Factor Investing

Edited by

Emmanuel Jurczenko

From Traditional to Alternative Risk Premia

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Foreword

Factor investing is not new. Investment factors were first identified in the 20th Century. What is new is that sophisticated quantitative models and an increased interest from market participants have turned academic theory into practical investment solutions.

One reason for the increased interest from clients has been deterioration in the forecast risk and return profile of traditional assets, most notably because of low yields. Meanwhile, standard alternative solutions such as hedge funds have too often been unable to provide satisfactory net-of-fees returns. Many investors have been drawn to factor investing in search of the returns they need.

At the heart of risk factor investing are the related ideas that investors are compensated not for holding assets but for assuming risks, and that diversification comes not from investing in different asset classes but from investing in the risk factors that drive these asset classes. Not all risk factors bring returns and it is the task of an investor to find which risk factors can be harvested as a premium.

This groundbreaking book represents a refreshing collaborative effort to define what factor investing really means, the risks and rewards associated with it and how best to implement those strategies. The book format offers an ideal mix of academic robustness peppered by practical common sense and implementation advice.

It contains 16 original and thought-provoking articles written by leading industry experts, with each chapter dealing with key aspects of factor investing:

– why some factors are associated with persistent outperformance while others are not;

– how predictable returns associated with these risk factors are, and how to assess their related systematic performance;

– how to integrate the practicalities of the market when implementing risk factor portfolios; and

– how to build strategic and tactical multi-factor portfolios, taking into account the complex risk profile and cyclicality of these factors.

The book also assesses some of the most recently documented risk factors such as cross-asset carry, volatility risk premia and factors in fixed-income markets, and explores extensions to long-short alternative risk premia investing.

As a result, this comprehensive volume is a powerful tool to help practitioners to keep abreast of developments in this fast-changing field, and transform academic factor theory into investable portfolios able to harvest potential risk premia effectively.

Fiona FRICK
CEO (Unigestion)

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Introduction

There has been tremendous adoption of factors by many institutional investors in risk management, portfolio construction, and as investment strategies. In 2016, the Economist Intelligence Unit surveyed 200 large, global institutions and found that nine out of ten of those investors are using factors in their investment management[1]. A large proportion of those institutions, particularly in Asia, conveyed their intention to significantly *increase* their use of factors over the next few years. Institutions are adopting factor investing so that they can better monitor their risks, construct more robust portfolios, and enhance returns or reduce risks compared to traditional benchmarks.

Factors are broad, persistently rewarded sources of return that we observe within and across asset classes. They include macro factors, like economic growth and inflation that drive the returns across major markets. Often, we describe the average returns of an asset class like equities or bonds by market capitalization indexes (which we often refer to as "the market"). Style factors, like value, carry, momentum, among other styles, typically identify certain types of securities using specific attributes. These style factors outperform the market on a risk-adjusted basis over a full market cycle. For example, stocks with low prices relative to fundamentals (value investing), securities with high income (carry), or trending securities (momentum investing), tend to beat the market over the long run. We observe similar patterns of outperformance for the same styles in equities, bonds, commodities, foreign exchange, and even in private market asset classes.

The title of this volume has the words "traditional" and "alternative" in describing factor investing. Factors are *traditional*: they result from economic rationales of a reward for bearing risk, a structural impediment, or investors'

Introduction written by Andrew ANG (BlackRock).

1 Economist Intelligence Unit, 2016, The Rise of Factor Investing.

behavioral biases [ANG 14]. They have been studied by academics and long practiced by investors. Value and quality investing, for example, date to *Security Analysis* first published by Graham and Dodd [GRA 34].

Factors are also *alternative*, in the sense that they can represent a differentiated return stream to traditional stock and bond market indexes. It is not the economic concept that is alternative; rather, what is new is the way we can employ these factor strategies in multiple markets, often transparently, and generally at lower cost than traditional active strategies. New research, data and technology, and advances in trading drive the new applications in investments, portfolio construction, and risk management.

This book emphasizes both the tradition and the new applications of factor investing. It ranges from the traditional to the alternative, discusses various challenges in adopting factor investing, and presents solutions in dealing with those challenges.

In Chapter 1, Inigo Fraser-Jenkins starts by laying out the implications for active managers and asset owners in the increasing take-up of factor investing, particularly in the long-only, index implementation of factor investing which industry now refers to as “smart beta”. Another form of factor investing is to directly focus on the factor premium by taking both long and short positions, and in doing so remove the effect of the market itself. In Chapter 2, Marie Brière and Ariane Szafarz examine the differences between the implementations of factor investing in smart beta (long only), full long-short, and intermediate positions between the two with 130-30 funds. In all cases, factor investing makes the distinction between traditional active and passive irrelevant: factors are like building blocks in that they can be assembled by different investors to meet different investment objectives.

How we construct the factors is an important question. Style factors, by definition, tilt to broad, persistent sources of returns and style factor portfolios take deliberate deviations from market capitalization weights. In Chapter 3, Jennifer Bender, Xiaole Sun and Taie Wang discuss the implications of moving from market capitalization weights in some factor strategies. Their analysis highlights the two decisions involved in constructing a factor portfolio: the subsample selected from the full universe and how those securities are weighted.

Further conditioning analysis on the factor portfolio is possible. In Chapter 4, Raul Leote de Carvalho, Xiao Lu, François Soupé and Patrick Dugnolle show how targeting a constant volatility for factors by hedging market exposures can improve the performance of factor strategies. There are also decisions to be made in the individual signals used in each factor: exactly how we measure the richness or cheapness in a value metric, for example. In Chapter 8, Jason Hsu, Vitali Kalesnik and Engin Kose explore the consequences of different choices of signals for the quality factor. Not surprisingly, different definitions lead to different experiences, and so the choice of signal, portfolio construction, and how these are implemented matter for investors.

A recurring theme is that factors are cyclical. Factor premiums vary over time, as we expect through their economic rationales. It is well known that predicting individual factor performance is difficult, especially done by timing only that factor. Chapter 5, by Robert J. Bianchi, Michael E. Drew and Scott N. Pappas, shows that combining different signals can lead to greater predictability. They caution, however, that the approach for signal combination is more effective for forecasting single factors compared to a portfolio of multiple factors. Yin Luo, in Chapter 6, shows how macroeconomic, market sentiment, capital markets and seasonal variables can be used to time factors.

Chapter 7, by Daniel Giamouridis, Michael Neumann and Michael Steliaros, shows how one proprietary signal, daily equity trading flow from the trades of a large broker-dealer, can predict factor returns. The corollary of their findings is that position-level factor information should also be used to monitor the risk of factor strategies. The different behavior of factors in different macro regimes is exploited by Olivier Blin, Florian Ielpo, Joan Lee and Jérôme Teiletche in Chapter 12. They consider regimes of recessions, inflation shocks, and periods of market stress, try to identify which regime prevails at a particular time, and rotate to attractive factors in that regime.

Factor premiums are observed in many asset classes. The majority of the academic literature has concentrated on equities, partly because of the longer time series and better quality. In Chapter 9, Demir Bektic, Ulrich Neugebauer, Michael Wegener and Josef-Stefan Wenzler apply factor investing to the corporate bond universe. Their paper is a cross-asset application of factors, using traditional equity market signals but applying these signals to the cross section of US corporate bonds. They show that size, value, and momentum effects are *broad*: these effects exist in bond markets as well as equity markets.

Carry and volatility risk premiums are factors that are present in several asset classes. In Chapter 13, Nick Baltas examines carry in commodity markets, equity markets across countries, and government bonds. He finds the returns of cross–asset class carry portfolios have relatively low correlation. While this is a challenge to building an encompassing theory of carry across all markets, the low correlations represent attractive diversification opportunities. In Chapter 14, Gregory M. McMurran, Megan Miller and Harindra de Silva examine cross-asset returns (in equities, commodities, bonds, and currencies) to volatility risk strategies – strategies which trade the difference between implied volatility in derivatives and realized volatility in the physical underlying instruments. There are again benefits in combining volatility risk premium strategies across asset classes.

Investors hold many different types of assets, and factors in liquid assets may constitute only one of many strategies in their portfolios. Thus, an important issue is how to construct an optimal portfolio using factors: which factors should an investor be exposed to, and in which assets and markets should that investor harvest those factors? In Chapter 10, Thierry Roncalli highlights that some factors, like carry and momentum, are negatively skewed. The skewness risk means that factor allocation is more complex than traditional asset allocation with mean-variance techniques. Skewness risk management is thus a key consideration in constructing optimal factor portfolios.

The factor insights extend to illiquid markets. In Chapter 11, Bob Bass, David Greenberg and Michael Kishinevsky show how to model macro factors in private assets, like real estate, private equity and infrastructure, consistently with macro factors in public markets like stocks and bonds. Their scenario-based analysis of factor returns is also a useful tool to handle the non-linearities present in factor strategies.

Investors may seek other outcomes other than enhanced returns, reduced risk, and superior diversification – the main investment outcomes that factor investing strategies are typically designed to achieve. In Chapter 15, Dimitris Melas, Zoltan Nagy and Padmakar Kulkarni explore the combination of factors with environmental, social, and governance (ESG) outcomes. ESG by itself has factor exposures, especially towards high quality and low volatility factor strategies, giving an ESG portfolio some historical outperformance relative to the market. With an optimization, they construct portfolios with both target factor and ESG exposures.

The last chapter of the book, by Nabil Bouamaraa, Kris Boudt, Benedict Peeters and James Thewissena comes back to the issues the book started with: the industry-wide implications for active managers and asset owners. While the authors focus on UCITS funds with one factor, momentum, the broader issue that they raise is the benchmarking of active funds in a world with factors – where the factors are well known, can be efficiently executed, and delivered in low-cost and tax-efficient vehicles. Factors simultaneously raise the bar for active managers, and deliver additional opportunities for asset owners.

Factor Investing: From Traditional to Alternative Risk Premia will be useful for the whole range of investors, from those beginning the factor journey to the sophisticated factor investor seeking state-of-the-art insights. Factors: not only going from traditional to alternative, but traditional *and* alternative. Indeed, the fact that they are both is why they can be so attractive for investors – and why the whole asset management industry is changing in response to the increasing adoption of factor investing.

Bibliography

[ANG 14] ANG A., *Asset Management: A Systematic Approach to Factor Investing*, Oxford University Press, 2014.

[GRA 34] GRAHAM B., DODD D., *Security Analysis*, McGraw-Hill, New York, 1934.

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The Price of Factors and the Implications for Active Investing

The cost of buying exposure to simple factors in the so-called smart beta format is rapidly declining. On one level, this raises the bar for all active managers (both fundamental and quant), but it also makes it easier to determine which kinds of returns investors should pay an active premium for. The price of buying smart beta is rapidly converging on outright passive rates, but at the same time this highlights that buying a smart beta index is an active act of asset allocation. When smart beta indices have a fee close to that of traditional indices, then they implicitly become benchmarks. This causes a profound shift in asset management: the progression from a univariate to multivariate benchmark. In such a world, the goal of active management becomes generating idiosyncratic returns.

1.1. Introduction

The pressure on active management from the rise in passive has been known for a long time. We think that a possibly greater influence in future will be the rise of commoditized factor strategies, first in long-only equities and then for cross-asset and long–short investment. We want to make it clear at the outset that we do not want to be seen as evangelists for smart beta; it is growing and will continue to grow, not because it is so wonderful or novel or because it represents any kind of intellectual breakthrough, but because it is cheap and disruptive. Ultimately, the purpose of the asset management industry, at its most basic level, is to give return streams to asset owners. The cost of one part of this (simple factors) is declining fast, and this means that assets should be reallocated to take account of this.

Chapter written by Inigo FRASER-JENKINS (Bernstein).

The growth of commoditized factors changes the asset management industry in a number of ways. In the end, it blurs the active–passive distinction and makes it difficult to say where one starts and the other ends, to the extent that active managers were offering return streams that looked a lot like factors. As such these cheap factor strategies offer a way to cut costs and should grow. We suggest that the price of commoditized factors will continue to fall. When the price of factors approaches the cost of buying the traditional cap-weighted passive index, a fundamental change occurs. At that point factors become plausible alternative benchmarks. What this does is essentially move the basis for assessing active managers. Historically the benchmark for nearly all funds has been a single index; we suggest the arrival of factors at close to zero fee makes the benchmark for all funds multivariate. This might sound like a nightmare for active managers, but actually we think it provides the basis for finding a core of active funds that are genuinely needed by investors. The measure for activity becomes idiosyncrasy. If a fund delivers returns that are idiosyncratic to the available set of commoditized factors, then it is probably important for the asset owner.

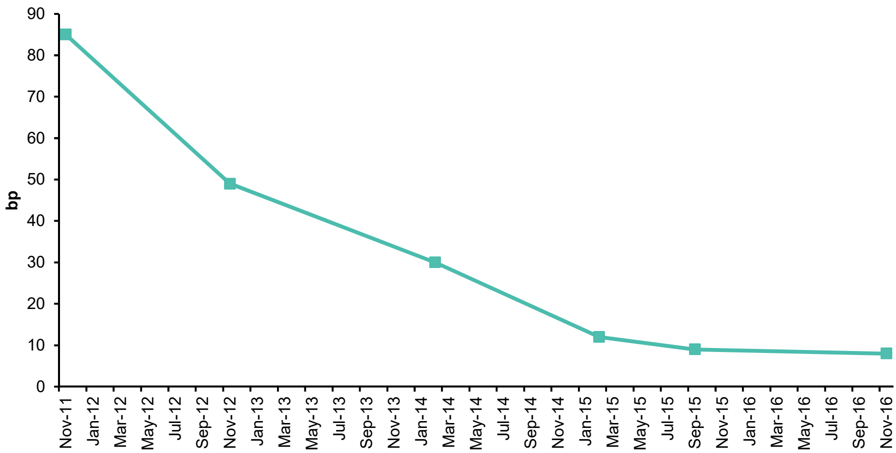
There is, however, a massive Achilles heel for smart beta. Who should get the job of allocating to these factors? This is essentially an act of asset allocation and is unambiguously active. Indeed, it can span asset classes. In a world where asset class returns are low and asset class correlations rise, the role of asset/factor allocation arguably becomes more important anyway. For most asset owners the ultimate benchmark is a liability set in the real world. Seen in that light, any allocation to a factor index or cap-weighted index is active. Thus for many investors, as factors become commoditized, the critical active factor question that they will face will be how to allocate to the factors rather than necessarily the best way of defining a given factor.

1.2. Smart beta: the Uber of asset management

At its simplest, commoditized factors allow for a cheap replication of some of the style factors that have been used by active fund managers to drive outperformance over the last 20 years. The "passive" replication of these factors by, for example, smart beta exchange traded fund (ETFs) provides a service for asset owners in lowering the cost for something that they no longer need to pay a full active asset management fee for. We believe that the best way to think about smart beta is as the Uber of fund management. It is potentially one of the main disruptive forces in equity investment, and its effects are likely to soon be felt in other asset classes too. It lowers costs for investors and democratizes access to a range of investment returns.

We should say upfront as a point of definition that we hate the phrase "smart beta". We have a lot of sympathy with Montier's pithy equality of *smart beta* =

dumb alpha + smart marketing [MON 13]. We do not want to be mistaken for evangelists for a smart beta approach. We also do not really care what it is called. We use the expressions alternative beta, strategic beta and exotic beta interchangeably, but we use the term "smart beta" here as that seems to be the most common one in use. It is just a marketing label. Smart beta is not going to grow because it is so good. The strategies used in smart beta are akin to active quant circa 1995. Nevertheless, smart beta is going to grow because it is so cheap. And it is becoming cheaper. In Figure 1.1, we show that the headline fees for smart beta are halving every year. In this case, we show the cheapest mainstream rate rather than an average across products.



NOTE: We have created this time series of smart beta fees from data on the pricing of some of the most popular smart beta products for large-cap US equities. The fees for international products tend to be higher. Data sourced as follows:
1) Powershares RAFI pre-2012 fee referenced in http://www.ft.com/cms/s/0/5133d548-3a3a-11e2-a32f-00144feabdc0.html#axzz3mdRjfaGM.
2) Powershares RAFI fee cuts of 21–36 bps referenced in http://www.ft.com/cms/s/0/5133d548-3a3a-11e2-a32f-00144feabdc0.html#axzz3mdRjfaGM.
3) The pre-2015 average fee level of State Street smart beta products as reported in http://www.ft.com/cms/s/0/cc2c12da-b04c-11e4-a2cc-00144feab7de.html#axzz3pEk5uFHY.
4) February 2015 price reductions for State Street smart beta products as reported in http://www.ft.com/cms/s/0/cc2c12da-b04c-11e4-a2cc-00144feab7de.html#axzz3pEk5uFHY.
5) GSAM active beta (multivariate smart beta) fees as reported in http://www.ft.com/cms/s/0/21831abe-61f3-11e5-9846-de406ccb37f2.html#axzz3pEk5uFHY.
6) Estimate of future smart beta fees based on the views of the potential buyers of such products.
7) Vanguard factor ETF as offered by www.nutmeg.com.
Source: Financial Times and Bernstein estimates (from November 2015 onwards) and analysis.

Figure 1.1. *Falling cost of smart beta: halving every year*

Here, we are taking a particular strand of smart beta, which is long-only, equity, US, ETF-format smart beta. But that is a large strand and anyway, the pattern holds elsewhere. This particularly strikes a chord in markets such as the United Kingdom and Australia, where fees have become the key issue above all others.

Smart beta has grown fast over the last 5 years, and we now estimate that within equities, it accounts for $500 billion–1 trillion of AUM. Although smart beta is large and growing fast, a lot more work is needed. We think we need to be explicit about what we need and what we do not need for the development of this area (see Table 1.1).

What we need	What we don't need
A process for strategic allocation to smart beta	Yet another new smart beta product launch with a new strategy or new weighting scheme. PLEASE, NO MORE INDICES.
A classification of smart betas	Another academic paper on why smart beta approach N will work because of behavioral bias X.
A measure of success of a given strategy	Please deliver us from consultants determining the allocation to these products.
A better name	Agonizing about whether they are active or passive. Who cares? The distinction is dead anyway.

Source: Bernstein analysis.

Table 1.1. *Smart beta: what we need and what we do not need*

Perhaps the most work needs to be done in the allocation process across smart beta. We do not necessarily mean dynamic or tactical switching: yes, we do see a growing appetite for that, but such tactical approaches will always be in the minority as proving skill at timing is hard. What is of more urgent need is a way of making a strategic or structural allocation to smart betas. At the moment, this is a mess and one of the areas we think most likely to give smart beta and quant in general a bad name. We see many cases where the investment in an often univariate smart beta strategy is pitched as a replacement to an active mandate with the aim of significantly lowering the fee. It may well be the right thing for an investor to replace a more traditional active mandate with a collection of smart beta funds, but moving to one smart beta probably makes a very significant change in factor allocation. We worry that end-investors at smaller institutions may not fully realize this. We worry more when this process is intermediated entirely by consultants as the evidence from academia implies that they may not be the best suited to make active allocations such as these [JEN 16]. The solutions teams of asset management businesses should take this out of the hands of consultants and help clients gain a better understanding of the benefits of taking multiple factor allocations rather than one.

What we do not need are more indices. Some organizations are already offering a plethora of indices. As an example, EDHEC proudly states that it offers 3,076 indices[1] and that is only one provider. Adding the indices available from other index providers and from ETF platforms means that there are now more smart beta indices than there are large-cap stocks that can be meaningfully invested in by investors. This cannot be an equilibrium solution. So our hearts sink when we hear that someone has launched a new smart beta index using some new screen, or some new weighting approach. What use is that meant to be?

We can all produce indices. We can line up as many screening factors as one likes. We can array as many weighting schemes as can be imagined and, hey, presto, we will have a superabundance of indices. Many of these may well outperform a cap-weighted index. So what? There seems to be some woefully mistaken belief that the next smart beta index will somehow add something that the others have not. One may as well search for the philosopher's stone.

Equally, we have become bored and dejected by the stream of academic or semiacademic articles explaining why smart beta index *N* will outperform because of behavioral bias *X*, or that someone has discovered a new "anomaly". What anomalies? "Anomaly" only makes sense if there is a prevailing paradigm in a Kuhnian sense, and we do not think that the efficient markets hypothesis retains enough credibility to be regarded as such.

The final thing we do not need is agonizing more about whether smart beta is active or passive. Our riposte to this is "so what"? The active versus passive distinction was good for the last 40 years of investment management, but the dichotomy has had its day and is no longer relevant. When more end-asset owners are adopting real-return benchmarks such as inflation, then any capital markets investment is active. Moreover, now we think there is a continuum of activity levels within equities and the distinction between whether strategy *A* is active or passive is a subjective one in the eye of the beholder.

In summary, there is a lot of hype about smart beta. This is right in the sense that it is a growing area, but it is growing because costs are falling so fast and it is "disrupting" some areas of traditional asset management. The growth of the last 5 years has been linked to the launching of new strategies, but the next spurt of growth needs more structure for allocating to such strategies and guidance for a way of thinking about such strategies.

What are the business implications of smart beta for asset managers? These vary depending on a manager's area of expertise. The provision of commoditized factors

1 http://www.scientificbeta.com/#/concept/betalab-indices-intro.

is now firmly in the same camp as more traditional forms of passive and is normally run by the same individuals; with headline fees on many of the products below 10 bps, this is a bulk-volume, low-margin effort.

There is still scope to charge a higher fee with more tailored or specialized versions of these strategies, but we think a larger opportunity may exist for the solutions businesses of asset management companies in putting together a strategic allocation to such factors. The other business opportunity for managers is to take market share back from index providers. For index providers, the growth of smart beta has been a fantastic opportunity to expand their business lines that had been based on traditional passive before. Nearly half of the new MSCI-based ETFs launched in 2014 were linked to MSCI factor indices. Moreover, for 2014, MSCI disclosed that assets either benchmarked to, or passively tracking, its factor indices totaled $122 billion, up 69% from $72 billion in 2013[2].

Asset managers have effectively ceded market share to index providers in this space for the last 3 years. There has been a tendency for asset managers to be happy to create a smart beta product that bears the brand name not of the asset manager but of an index provider. There have been several reasons for this. For one, as these products have been sold as semipassive, just having an index providers' brand name has been important for gaining the trust of the investment committees of some investors such as small pension funds. Another reason is that it has often been the passive teams within asset management companies that are launching indices such as this, as opposed to traditional active teams. However, we think that investors are starting to look through this simple labeling. A bigger reason for managers to fight back against this model is due to the fee level. When the fees on these products were above 20 bps, paying 3 bps to an index provider to use their name on the passive replication of a factor index might have been okay. But with fees now below 10 bps and falling, this no longer makes business sense. We see this in GSAM's Active Beta product[3] as an example of, in this case, a multifactor smart beta product that is branded with an asset management name as opposed to an index provider. An area that still needs to be explored is what level of product complexity is possible for a product to still be called smart beta. There is no firm answer to this. At the moment, the index provider based products still predominate at the most simple end of the spectrum, but this could change. The other business opportunity is for the long–short version of smart beta, which we turn to later.

2 MSCI annual report at http://files.shareholder.com/downloads/MSCI/1406858044x0x816421/CB97F084-029B-4EB8-8330-ACAC47F44904/2014AR_832959_019_MSCI_BMK.PDF.
3 https://assetmanagement.gs.com/content/gsam/us/en/advisors/resources/investment-ideas/active-beta-etfs.html.

1.3. Allocating to smart beta: an unambiguously active decision

One of the most pressing current issues with smart beta is how the decision is made to allocate to such strategies. For an investor benchmarked to the traditional cap-weighted index, any allocation to smart beta is an active decision, and for an investor with a "real" benchmark or matching a liability, the allocation to equities in the first place is an active decision.

We worry that so far this has been done poorly and does not receive the attention that it deserves. Smart beta products, in theory, provide an opportunity to make strategic allocation to factors in the market and also to make tactical allocations where people think they have skill in that area. But this begs several questions. Who gets the job of making this allocation? Is it done well? If one is strategically allocating to a number of smart betas, would it be better to instead allocate to a proper multivariate quant strategy? How is this allocation process likely to evolve? What is the allocation process worth in terms of fees?

What really worries us is when end-investors (e.g., small pension funds) take large positions in just one smart beta product in a bid to cut active management fees. Making such an allocation could be very active in practice, but could be presented as an allocation to an almost passive position. We think that such investors making such one-off allocations need help in understanding their factor risks and the implications of this in certain macro environments. We see that in many cases, pension fund consultants are guiding these allocations, and indeed a large part of the push for the expansion of low volatility was consultant-led.

A survey of 181 asset owners by Russell Indices in early 2014 indicated that the information from index providers and consultants played a dominant role in the decision to initially evaluate smart betas (although the same survey suggested information from asset managers was a dominant deciding factor more in the evaluation stage). Such huge dependence on index providers to make what could be a very active investment decision is, we think, odd. Also, academic evidence has started to emerge suggesting that consultants are not well-placed to make this kind of fund allocation decision. For example, Jenkinson *et al*. [JEN 14] find that:

> "Focusing on US actively managed equity funds, we analyze the factors that drive consultants' recommendations, what impact these recommendations have on flows and how well the recommended funds perform…we find no evidence that these recommendations add value, suggesting that the search for winners, encouraged and guided by investment consultants, is fruitless".

From a financial stability perspective, the Bank of England has drawn attention to the potential herding issues associated with these recommendations: "A survey by the National Association of Pension Funds (NAPF) undertaken in early 2014 found that 50% of U.K. workplace pension funds surveyed were advised by the three largest investment consultancies, and the top six consultancies accounted for around 70% of the schemes surveyed" [4].

This may be changing as more asset managers build out solutions businesses. Logically, more asset managers should move into the field of strategic and tactical allocation across smart beta as that gets back to active management with an ability to differentiate performance and earn at least some of the associated fees. We expect much more competition in coming years in the business of allocation to smart betas as the fees on the underlying products continue to fall.

A trend in recent years has been that index providers have directly or indirectly taken a considerable market share in the business of the underlying smart beta building blocks. This appears to be due to these products being sold as if they are passive products. Hence, the index provider brand name has been of paramount importance, especially when pitching to pension fund boards, etc. Another reason for market share gain by index providers could be their prominence in the process of making many asset owners initially aware of the smart beta option. We would not be surprised if this began to change as investors come to realize the importance of more sophisticated approaches to portfolio construction and factor combination, and as asset managers become more prominent in the marketing of such products.

Some investors take a strategic view that they wish to allocate to factors that have displayed efficacy on average in the long term. For example, factor groups such as value, quality and momentum tend to outperform in the long term, and so an investor could reasonably conclude that a default position that had exposure to these three factors should be a good basis for investment and even a possible benchmark for assessing the performance of more active strategies. It is also apparent that there is a desire to move on from the "first wave" of smart beta products, such as minimum variance and fundamental indexation, which are all univariate in nature. Any univariate product is expected to underperform at some stage in the cycle.

There is the age-old topic of how to combine factors. Investors face a choice of buying prepackaged indices, or "properly" bringing the factors together in the way that is traditional for quant models. This would involve measuring the exposure of each stock to the factors of interest and forming a return forecast on the stock as a (usually linear) weighted combined product of factor coefficients and factor exposures. Quants may shrug their shoulders at this point and assume that they won

4 See Procyclicality and structural trends in investment allocation by insurance companies and pension funds: A Discussion Paper by the Bank of England and the Procyclicality Working Group, July 2014.

the argument in favor of combining factors at the single stock level decades ago, so they may wonder why the argument is even taking place. The deciding element in which approach to go with though is not just about maximizing return/risk, there is also a governance angle that is crucial as we discuss in the following.

The combination of factors at the individual stock level has many advantages. It allows for a much more sophisticated approach to portfolio construction to better reflect risks and for differentiation in approach by sector if needed. Most importantly, it allows one to benefit from combination effects in terms of factor exposure at the stock level, for example, capturing nonlinear effects present in the combinations of factors. More prosaically, this “proper” combination approach tends to outperform.

However, the combination of prepackaged building blocks will probably play a role, especially in the hands of a passive funds sales force. It may gather assets despite theoretical and empirical shortcomings. First, it is desperately simple – one typically just chooses some prepackaged univariate factors and puts them together in a portfolio. Simplicity should not be knocked; it has a lot going for it in pure commercial terms. Second, it can be made really cheap. If the going rate for the underlying signals is currently of the order of 10 bps and is swiftly heading to low single digits, then the building blocks have close to passive rates. This approach also allows composite portfolios to be formed that combine indices based on cross-sectional equity approaches alongside index-level strategies. An example of the latter case would be if index-level short volatility strategies were added to a portfolio of value and quality funds. This second approach also allows for factors to be tactically timed at a faster rate, should one wish to do that, as the underlying products could be largely in the ETF or swap format.

We have seen products start to emerge that offer this simple combination of strategies. They fit within the framework of offering a simple product, which is what already attracts a significant part of the investor base into smart beta. State Street has structured an ETF on an MSCI Index called “quality mix” that is simply a combination of three factor indices: value, low volatility and quality[5]. More recently, GSAM has also created a similar product with the delightful name of “active beta” (a proof of the end of any active–passive distinction; maybe that was Goldman’s point?). This brings together value, momentum, quality and low volatility[6]. We think there are two interesting things about this product. First, the fee for its US version is being set at just 9 bps. Second, GSAM is using its own indices and not taking them from an index provider. A motivation for that might be simply to save on license

5 https://www.spdrs.com/product/fund.seam?ticker=QEFA.

6 John Authers: Goldman makes an ETF splash with low fees, *Financial Times,* September 24, 2015.

fees, but we think it might become part of a broader trend of asset managers fighting back against the attempts of index providers to take market share in this area.

Quants will probably turn their noses up at approaches that combine prepackaged indices, and especially if they are simply equally weighted. However, quants should be aware that whatever the theoretical advantages of running the factor combination at the individual security level, by combining prepackaged indices some smart beta approaches can enjoy an advantage when a pension plan board has signed off on wanting to always have exposure to given "risk premia". It might not be the optimal solution, but it might be the one that best fits some mandates. Thus, we think that there may be a clientele effect whereby some investors want a very cheap (sub 10 bps), simple product, while others will pay for superior portfolio construction and factor combination.

1.4. Adoption of smart beta

So who is buying this stuff? The initial take up has been stronger among asset owners in Europe than in the United States or Asia. But we expect this to change. The Sovereign Wealth Fund Institute, in October 2014, conducted a survey of 72 public institutions with over $2.9 trillion in public investor capital represented. "Among the public institutions surveyed, 67% claim to already have smart beta allocations, or are in the evaluation process. Of the sovereign wealth funds in the sample, 37% say that they have allocations, while another 25% say that they are currently evaluating a smart beta strategy". MSCI estimates that assets utilizing smart beta strategies have grown from $20 billion in 2005 to $500 billion today (August 2015)[7].

Investment & Pensions Europe, in February 2015, conducted a survey of European pension funds, which collectively manage almost $200 billion in assets[8]. Over half the respondents currently allocate to smart beta investments, and allocations are normally significant — eight respondents have allocated 20% or more of their equity portfolio to smart beta[9]. The long-term investment horizons for sovereign wealth and pension funds are particularly suited to smart beta allocations as they can withstand cyclicality in factor performance.

7 http://www.sovereignwealthcenter.com/Article/3441523/SWFs-Are-Hot-for-Smart-Beta-What-Does-That-Mean-For-Stakeholders.html#.VgUIsjdOVzM.

8 http://www.ipe.com/reports/smart-beta/focus-group-pension-funds-get-smart/10006906.fullarticle.

9 IPE.com.

Gaining cheap exposure to systematic risk factors rather than trying to seek out traditional "alpha" is a driving force in the adoption of these strategies. As an example of the thought process that we come across among asset owners making this switch, Tomas Franzén, chief investment strategist at Swedish pension fund AP2 was quoted in the *FT* as saying, "It's not that we think alpha doesn't exist. But it would be naive to think that alpha would be cheap…and it's also difficult to identify those managers and then knowing if the alpha will persist"[10]. The $51-billion Alaska Permanent Fund Corporation had 8% of its equities devoted to smart beta or similar strategies as of June 2014[11], and the CIO was calling for further investment, saying to the fund's board of trustees that "Today's alpha is tomorrow's smart beta"[12].

While the Dutch and Nordic pension funds were the early adopters of smart beta, the Sovereign Wealth Fund Institute survey suggests that smart beta is making inroads with funds in the Middle East and Asia. Japan's $1 trillion Government Pension Investment Fund (GPIF), which has also adopted smart beta, has also made inroads in this area. In April 2014, the fund announced a revision in its management structure, which overhauled its equity investment strategy[13]. It reduced its passive market cap investments based on the Topix index and added the JPX-Nikkei 400 index, which is designed to encourage investment in stocks with high return on equity and good governance. The fund also trimmed traditional active investments to make room for smart beta strategies, awarding three new mandates. What is interesting is that it is different from the cost-cutting or efficiency reasons often cited by asset owners making this switch elsewhere. In the case of Japan, this was explicitly to try to bring about corporate change, to influence the management of Japanese companies and to increase the profitability of the Japanese corporate sector. Thus, a very different motivation has led to the same result. While, to our knowledge, Japan is the only jurisdiction to adopt such a normative approach, the GPIF adopting smart beta strategies has provided a huge boost to confidence in the sector in the region.

The most popular types of smart beta so far have been low-volatility investments and fundamental indexation, and the indications are that these will continue to enjoy strong momentum in asset gathering. A recent survey by Russell showed that these two strategies continued to take the lion's share of strategies being evaluated (see Table 1.2). After these two come quality investments, followed by a range of others. Although this shows the popularity of univariate strategies, we expect more of the

10 http://www.ft.com/cms/s/0/eac0a3e8-83e8-11e1-9d54-00144feab49a.html#axzz3pBLpoe7N.

11 http://www.sovereignwealthcenter.com/Article/3442985/Smart-Beta-Promise-and-Pitfalls-for-Sovereign-Wealth-Funds.html#.VijimjeFNi5.

12 http://www.institutionalinvestor.com/article/3457741/investors-sovereign-wealth-funds/why-sovereign-wealth-funds-love-smart-beta.html#.VijhejeFNi5.

13 http://www.gpif.go.jp/topics/2014/pdf/gpifs_selection_en.pdf.

innovation (and probably more asset manager revenue) to come from more sophisticated versions of these or multifactor versions as asset owners become more comfortable with the concept and as fees on univariate products fall further.

	US	Europe ex UK
Low vol/minimum variance	54%	81%
Fundamental Indexation	61%	59%
Quality	32%	44%
Risk parity	25%	37%
Momentum	25%	26%
Equal weighting	25%	44%
Income	21%	41%

Source: Smart Beta, Russell Indices 2014 and Bernstein analysis.

Table 1.2. *Types of smart beta currently under evaluation*

A final nugget on the practical application of these approaches is worth noting. We have found anecdotally that smart beta products are viewed as competitors to both active and passive funds. The same Russell survey supports this point, with more asset owners reporting that they view smart beta as a replacement for passive mandates than as a replacement for active mandates (see Table 1.3). But the largest number of respondents saw such strategies as a replacement for both active and passive mandates. We think this supports our thesis of the end of an active–passive distinction.

Smart beta can replace either active or passive	44%
Smart beta replaces only passive	32%
Smart beta replaces only active	21%
Neither a replacement for active or passive	3%

Source: Smart Beta, Russell Indices 2014 and Bernstein analysis.

Table 1.3. *Smart beta can replace both active and passive mandates*

1.5. Organizational issues for smart beta

Asset managers are only in the early stages of figuring out the questions that are begged by the importance of smart beta and risk premia strategies for corporate structure. What are the personnel implications of these strategies? Who gets to run them and how do they relate to the more traditional parts of an asset management organization? This is one specific example of the broader impact of the end of a hard distinction between active and passive mandates. There used to be a clear division between a passive department and an active department, with maybe quants as a separate group or within active, or else a separate enhanced index group. We think that this is no longer an equilibrium solution. Equally, there is almost certainly no one optimal arrangement here, as it depends on what function smart beta serves in an organization, i.e. is it integrated within a range of alternative fund offerings? Is it there to generate large passive AUM volumes? Is it even seen as simply a cushion to slow active outflows?

To date, passive departments have dominated in the construction of the underlying smart beta products, particularly as, in many cases, such products are explicitly based on third-party (i.e. index provider) strategies. In this case, the role of the asset manager is simply to make an index investible (and, of course, to market it). The role of the passive departments will, in the near term, no doubt remain significant as the key point of competition for many in this area at the moment is price. So, massive scale and cheap passive implementation is necessary.

However, for some managers, this may change. We suspect that there may be an advantage in offering more sophisticated approaches to factor formation, factor combination and portfolio construction – in which case, it is closer to the natural domain of "active" quant groups — or else in treating these as allocation building blocks – in which case, it may be closer to the natural domain of strategists and asset allocators. We very much respect the view on this expressed by Pascal Blanqué, Deputy CEO and CIO of Amundi [BLA 14]:

> "…since the subject is ultimately the correct, multifactor allocation at the overall portfolio level, one realizes more naturally that this [smart beta] comes within the jurisdiction of a "strategy" team, which has a good overview and is, for example, able to arbitrate the simultaneous presence of a given factor within different pockets, which come under the control of distinct entities (classic passive, active, smart beta), thus placing the indexed department no less naturally in an implementation/execution role."

1.6. Toward idiosyncratic returns

We think that the declining cost of buying factors is subtly, step-by-step, leading to a world where the benchmark that managers are measured against has become multivariate rather than univariate. Yes, we know that very few people think like this at the moment, and the whole selling and regulation of the industry is predicated on a univariate benchmark. But we think that as the cost of factors converges on the cost of buying a passive index, benchmarks will become multivariate whether people like it or not. This leads to a world where the key measure of success in fund management becomes the ability to generate idiosyncratic returns, i.e. returns that are different from a linear set of systematic factors.

We think that asset owners will need this kind of return stream and will continue to pay for it. Thus, the focus for asset managers should be in the manufacturing of such returns and finding a clear way to market the results. We think that in this lies a good defense of active management. It is, however, a defense with caveats. Funds that are not able to demonstrate such returns, and there may be many of them, are likely to come under sustained pricing pressure and see outflows. Yes, active management may be under pressure from passive and semipassive strategies, but we think that the pressure will be felt in a very non-uniform way. Furthermore, if we are right to believe that we are in a low-return world, then asset owners are going to be dependent on asset managers for generating the return stream that they need.

1.7. The role of benchmarks: has the benchmark triumphed, or is it dead?

Most readers will have spent their whole careers in an environment dominated by benchmarking. This comes via two routes: the rapid increase in passive benchmark tracking and the culture of all active fund performance being expressed as benchmark relative. The ubiquity of benchmarks may make them seem triumphant, yet we see a counter trend emerging in the realization that the ultimate benchmark is always something other than an index based on capital markets.

Expressing fund returns on a relative basis and the popularity of the passive market-cap-weighted benchmark are two sides of the same coin. Yes, of course, such benchmarks are important. They are needed because: (1) one wants to know if a manager's active decisions were better than a more simple approach, and (2) buying the simple approach is cheap.

But statements (1) and (2) could apply to many benchmarks, not just the one based on the market-cap-weighted index. What we are seeing with the rise of assets linked to smart beta indices is this argument being applied to other simple ways of investing.

We think this is a logical extension of the benchmarking wave of the last 30 years. In fact, now that it is happening, one is inclined to wonder why it took so long.

On the one hand, this cements the rule of benchmarks, but it also sounds the death knell of the market-cap-weighted benchmark being the only one. We are not arch-relativists when it comes to benchmarks. We do recognize that the market-cap-weighted index does indeed have a special role as it is, by construction, the only index that everyone can go and buy. However, when there are other benchmarks that are available at the same price point, for all practical purposes, it should not have such a special role.

However, we profoundly worry that all this benchmarking is one monumental mental short cut by the investing world. Yes, humans love mental short cuts; psychology literature has taught us as much. While they are important for surviving on the African savannah, it might not always be the route to an optimal portfolio allocation. The problem, of course, is that benchmarks in the form of financial indices are very poor proxies for actual benchmarks that end-investors face. We love Pascal Blanqué's comment on this and could not put it better ourselves [BLA 14]:

> "Presenting passive and/or benchmarked active management as a cautious way to reduce and manage risk is one of the biggest lies in investment management – the actual confusion between simplicity, or even transparency, caused by benchmarks and risk neutrality proved to be an intellectual mistake and was evidence of complacency on the part of most governance bodies, since it ended in tears".

If one starts from the point of view that all investment is to fund some real activity (i.e. to provide income in retirement for an individual or as a strategic investment by a state), then the ultimate benchmark is probably closer to something like a spread over inflation measured in a certain country, or maybe a set nominal return each year.

If this is the benchmark, then all investment in financial indices is active. The decision to buy a "passive" tracker on the S&P 500 or a smart beta value index, or the stock of one company, is active. This is an alternative way to come back to our thesis that the active–passive distinction is no longer clear and is, in fact, subjective. If more investing moves this way, then it is also likely to change the way those benchmarks are used.

Finally, we note that staying close to equity and bond benchmarks has been attractive over the last 40 years, when both asset classes delivered positive returns and at the same time managed low and even negative correlations. In the short term, these assets can deliver returns that are linked to the evolution of the economic cycle, but with high starting equity multiples (on Shiller PE at least) and low bond yields that we see today it is hard to support the case that the strategic returns from these asset classes can be maintained at the same level. Moreover, the correlation of stocks and bonds has historically shown a link with inflation. As inflation starts to rise, the negative correlation of the last decade may well flip to positive correlation. In such a low-return but high correlation world, the attraction of simply allocating to a benchmark may wither and, indeed, seen in the context of the need for asset owners to meet their liabilities, 60:40 could become more risky.

1.8. Idiosyncratic returns: the emergence of a multivariate benchmark whether one likes it or not

As the active–passive distinction evaporates, a more relevant question is what kind of activity can an "active" manager offer? First, our basis for saying that the active–passive distinction no longer exists is the growth of products that lie in between the two and also the increased adoption of real benchmarks by asset owners, which mean that the decision to buy any capital markets product is an active one. However, if a given benchmark is specified, then within equities there are broadly three categories of activity that are possible:

– strategic factor exposure (i.e. a persistent factor bias that is not timed);

– timing (e.g. of market risk, factor risk and themes);

– stock picking.

The emergence of cheap, commoditized factor products at passive fee levels has brought about a subtle, but significant, change in the industry. We have moved out of the univariate benchmark paradigm of the last 30 years to a multivariate benchmark world, where the smart betas have become benchmarks. Importantly, it does not matter if one hates smart beta or does not accept such approaches. Smart betas or commoditized factors are becoming benchmarks because they are so cheap (<10 bps fees for ETFs on US products and even lower fees for segregated accounts). As we have said earlier, we think the right way to think about smart beta is not as being "smart" in any way, but as being an equivalent of a disruptive Uber in fund management. Investors do not yet think this way, but we think that it is the imperative of lower costs that will drive this change.

What this leads us to is that we think there are three axes of fund activity that are needed to map out managers and distinguish their sources of activity and ultimately their type of skill: tracking error, active share and idiosyncratic risk. The latter is the share of a fund's activity that comes from sources of return not captured by strategic exposure to systematic risk factors. We measure the idiosyncratic component of returns by running a regression of a fund's return on the market return and a set of risk factors and then our measure of idiosyncrasy could be thought about in two ways:

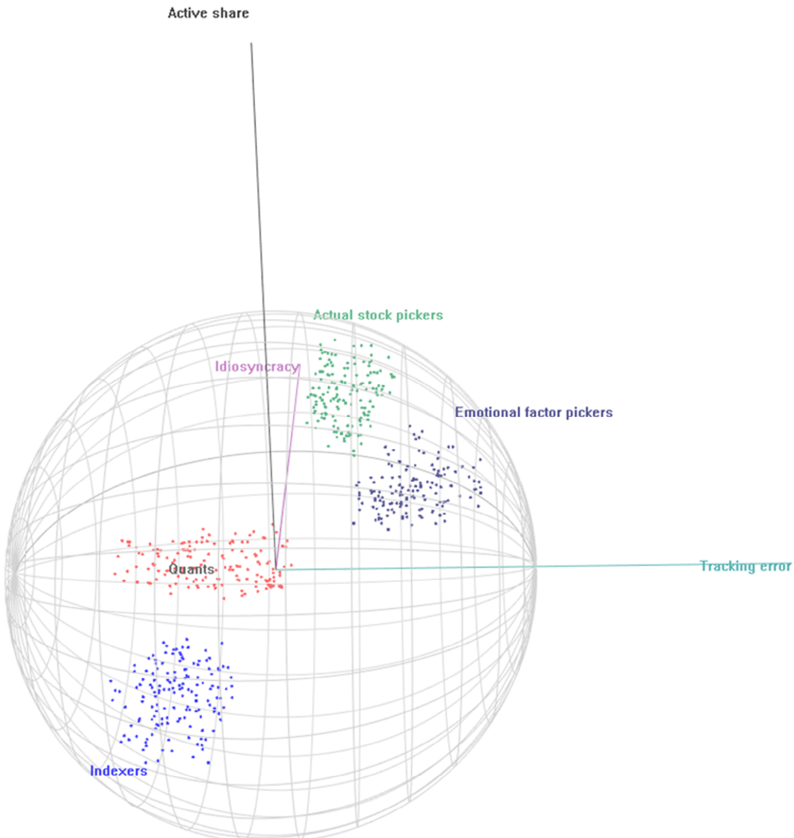
– 1 – R^2 from the regression;

– or for those who prefer a tracking error type measure, it could be thought of as the standard deviation over time of the residuals from such a regression, i.e. an N-dimensional analog of tracking error.

There are various subtleties in running this regression. One question that arises is what factors should one use as the set of regressors? We think that it should not be the Fama–French factors, or the standard quant answer of the factors that span the cross-section of return (one cannot know what they are in the next period, one cannot buy them and it is complicated and time varying). Instead, we would rather take a much more prosaic approach and just use the set of factors that are cheap and liquid, because this is not a quant question about the best way to explain portfolio returns but a marketing question of how to position active funds. We note that rewarding a manager only for what was not explained by such a regression would do managers who got their factor allocation correct a disservice. The regression will assign coefficients to each factor in such a way to best describe returns over the sample period, but those factor weights could not have been known *ex ante* and are valuable. Hence, the coefficients have to be constrained or defined predicated on some prior period.

We show these three axes of activity in Figure 1.2 along with suggestions of where manager groups might lie. Quants usually have low active share, will have a tracking error that is likely to vary from low to middling, but can achieve idiosyncratic returns. Therefore, they can aim to be in the back half of the sphere. The real distinction comes within the universe of fundamental (non-quant) funds, where we distinguish between actual stock pickers, who have a high active share and tracking error and also high idiosyncratic returns, and what we call "emotional stock pickers". The latter group looks like they are active because they have high active share and high tracking error, i.e. the measures that many consultants and regulators use to assess whether someone is really active. But for this group all of this comes from taking exposure to a linear combination of systematic factor. They might even *think* they are picking stocks, but without realizing it, they are just inefficiently reproducing factors. While the former group has, we think, a stable outlook and no need to reduce their active fees, it is the latter group that is going to come under pressure both on pricing and in terms of reputation in an environment where market participants are aware that simple factors are available cheaply. We suspect that there could be a lot of funds in this latter group.

For the group that we term emotional factor pickers, the situation could be even worse than that. If they believe that what they are doing is picking stocks when they sit down with their marketing department, they may conclude that what they should be doing is maximizing active share and producing a concentrated portfolio. However, if what they are really doing is running a *strategy*, then what they should do is diversify out a single stock risk and adopt an approach for portfolio construction that purifies their exposure to the strategy. Thus, they could be using the wrong construction approach.



Note: Figure shows where different groups of asset managers are likely to lie on three axes of investor activity: tracking error, active share and idiosyncratic returns. Tracking error is defined as the time series standard deviation of deviations in return from benchmark. Active share is one-half of the sum of absolute weight differences between the portfolio and its benchmark, while idiosyncratic returns captures the proportion of returns that are not due to common style factor exposures. The clusters of points indicate where we believe different managers lie. For example, indexers have a low level of activity on all three measures and actual stock pickers have a high level on all three measures. The group of investors who have high active share and high tracking error but only exhibit low idiosyncratic returns, we call emotional factor pickers. For active quants, we suggest the goal is likely to be high idiosyncratic returns, low active share and a range of tracking errors from low to medium dependent on risk budget.

Source: Bernstein analysis.

Figure 1.2. *A spherical classification of active managers. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

But how can one think about the relative contributions of these elements? How are tracking error, active share and idiosyncratic returns linked? Amihud and Goyenko [AMI 13] distinguish between what they call "selectivity" and "active share". Their definition of selectivity is similar to our definition of the idiosyncratic risk in the sense that it is $1 - R^2$ from a regression of a fund returns on a set of factors (in the Amihud and Goyenko paper they use the Fama–French factors, whereas we would prefer a different set as we have described). They point out that selectivity and active share are similar but not the same. They will differ, for example, if:

– a fund deviates from its benchmark by taking a position in a different (passive) index. In this case, active share would rise but selectivity would not;

– likewise, if a single stock outside the benchmark index is added that has a perfect correlation with the stock that it is replacing, then active share will rise but selectivity will not, i.e. active share does not account for the correlation of securities that are held in the fund.

A way of thinking about the relative scale of the inputs and their relationship is to decompose active risk or tracking error. We can write:

$$\mathrm{TE} = \sqrt{\text{systematic risk}^2 + \text{idiosyncratic risk}^2}$$

Sapra and Hunjan [SAP 13] show that through this approach we can separate the expected value of the tracking error into a term that is dependent on a sum of systematic risk factors and a term that is dependent on active share and the idiosyncratic risk of stocks. So, expected value of tracking error becomes:

$$TE = \sqrt{b'Wb \quad + AS^2 \frac{2\pi}{N} \overline{\sigma_e^2}},$$

where b is the portfolio exposure to systematic risk factors, W is their mutual covariance, AS is the portfolio's active share and $\overline{\sigma_e}$ is the average idiosyncratic stock risk. Note that this only works if the latter term is the idiosyncratic risk of stocks, as the total risk of each stock would include both a systematic and idiosyncratic element. For completeness, we would choose to add an extra term for the timing of systematic factors. Equations of the form $z^2 = x^2 + y^2$ map out a curved cone shape, but the terms are constrained to one quadrant of a cone because of the range of values that factor exposures and active share can take. Thus, we can think about the tracking error of a fund as lying somewhere on such a surface with its position defined by a systematic factor term and an active share × idiosyncratic risk term.

Our point here is that not all tracking error is equal. Yes, we have known this in theory for ages, but it is product pricing that is making this more important.

Mapping out funds in this way is no longer just an issue of risk management; it now also becomes an issue of fund pricing.

A significant problem with rewarding managers only for the part of their return that is unexplained by a simple regression of fund returns on factors is the question of rewarding the managers who get the factor call right. To that end it may be desirable to split out the returns that come from strategic exposure to factors versus those that come from factor timing. There are various ways of doing this, one example is Chen *et al.* [CHE 09][14]; they suggested model accounts for static and tactical market and factor exposures:

$$r_{i,t} = \alpha_i + \beta_i RMBF_t + s_i SMB_t + h_i HML_t + p_i MOM_t +$$

$$\gamma_{1,t} RMRF_t^* + \gamma_{2,t} SMB_t^* + \gamma_{3,t} HML_t^* + \gamma_{4,t} MOM_t^* + \varepsilon_{i,t}$$

$$RMRF_t^* = I\{RMBF_t > 0\}\, RMBF_t$$

$$SMB_t^* = I\{SMB_t > 0\}\, SMB_t$$

$$MOM_t^* = I\{MOM_t > 0\}\, MOM_t$$

$$HML_t^* = I\{HML_t > 0\}\, HML_t$$

where α_i is the abnormal return of the fund i; $r_{i,t}$ is the excess return of the fund i; *RMBF* is the excess return of the market; *SMB*, *HML* and *MOM* are returns on value-weighted, zero-investment, factor-mimicking portfolios for size, book-to-market equity and 1-year momentum; and *I{condition}* is an indicator function that equals one if the condition is true and zero otherwise. Thus, β captures market exposure; *s*, *h* and *p* capture size, value and momentum exposure, respectively, while $\{\gamma_{1,t}, \gamma_{2,t}, \gamma_{3,t}, \gamma_{4,t}\}$ capture the ability to time the market and factor size, value and momentum. This is fine as far as it goes. Although it can be easily extended to include other factors such as risk and quality, it is tricky to extend this methodology to all the themes that portfolio managers may wish to dynamically allocate to in practice. Also, determining what counts as a strategic thematic exposure versus single stock selection is not always clear.

In general, we could write:

Fund return = stock selection + market exposure + factor/theme exposure + timing ability,

where the timing ability term is broadly defined as the skill in seeking out market, factor or thematic opportunities. There will also be other elements that could

14 See: What style timing skills do mutual fund "stars" possess? Available at http://ssrn.com/abstract=1362086.

arguably be included, such as terms for portfolio construction, factor interaction and portfolio implementation. Writing this has an implication for fund pricing as we can observe the market rates for these inputs and that some of them have changed. Buying passive market exposure is now essentially free for large institutions. As discussed earlier, the fee on simple smart beta is now about 10 bps for the US market and is falling, whereas actual stock picking ability or timing ability is worth a lot.

The broader point here is that quant is changing the rules of the game for all fund management. There has been a subtle shift in the last couple of years from a univariate to a multivariate benchmark. Not everyone realizes this yet. Importantly, it does not matter what the fund prospectus says the benchmark is, or that regulation specifies that a single benchmark is identified or that the manager may dismiss smart beta and disagree with the notion of commoditized factors. The multivariate benchmark of cheap factors is now a fact of life because these factors have a cost that is close to that of the traditional cap-weighted benchmark.

1.9. Opportunities for asset managers and asset owners

Some asset managers may get to this stage and find our world view thoroughly depressing. It is not meant to be! Yes, the opportunity set is changing, but we think that the role of the asset manager is alive and well. We think there are various areas of growth, which will appeal to different parts of the industry depending on their strengths:

– Smart beta: This will continue to see asset growth, though fees will also continue to fall at a fast rate. So, this will rapidly become a volume “game” and, hence, appeal to a certain category of asset manager, though there will be some ability to charge a premium for more sophisticated approaches. As investors become more discerning in this area, there should be an opportunity for asset managers to take market share with their own branded products away from index provider based products.

– Risk premia: We see this as distinct from smart beta in that it tends to be long short and also cross-asset. We see continued growth in this from a very small base. At first, we think, this will mainly appeal to sophisticated asset owners (large pension funds and Sovereign Wealth funds (SWFs)), though, in time, the same products could also be used for hedge fund replacement strategies. This provides a possible opportunity for more traditional asset management companies that have quant departments.

– Strategic factor allocation: The role of asset allocators and “investment solutions” departments should expand into advice on how to build portfolios from these newly emergent strategies and products. We think that asset managers will have an opportunity to take market share from consultants in this area.

– Tactical factor allocation: As these products become cheaper to trade, it is natural that some investors will wish to use them to dynamically change factor exposure over the cycle. Although equity quants have had a go at factor timing for years (decades?), applying this to the cross-asset risk premia space is new and we have not seen products with long track records. But this will evolve.

– Dynamic allocation: We can think more broadly than the narrow question of tactical factor allocation to dynamic allocation to risk or themes. This is, after all, one of the key aims of many fundamental fund managers. Themes can take hold in the market and become a significant variable in the cross-section of returns for a time. Identifying these correctly will always be something that asset owners should be willing to pay for.

– Stock picking: Real, true stock picking (by which we mean idiosyncratic returns apart from those generated from dynamic thematic, sector or factor allocation) will also always be valuable. It is only a small minority of investors who can achieve this and that many people who think they are picking stocks are really just running a strategy, but those who can, will be able to charge a premium.

What will not work?

We worry that funds that do not offer idiosyncratic returns (i.e. are not effectively dynamic, or do not pick stocks over and above a simple linear combination of systematic factor exposures) may suffer.

And for asset owners? There are opportunities for asset owners as well:

– Cut costs: The decline in smart beta fees and the impact that this will eventually have on “active” funds will allow them to reduce their payment in some areas and focus on spending money where it is most valuable to them.

– Understanding factor risk: Evaluating managers against a broad factor set in addition to the market will facilitate a much better understanding of factor exposures.

– Diversification: Both cross-asset risk premia products and intra asset-class smart beta products could possibly allow for better diversification in that the correlation of factors would appear to be more stable than the correlation of asset-class indices.

– Returns: In a low-return world, cross-asset risk premia may be an invaluable source of returns, when long-only asset-class level indices offer limited returns compared to the returns that are expected or compared to the ultimate liabilities.

– We worry that the falling cost of smart beta might lead to an undue focus on fees above other considerations, whereas the active decision of factor exposure and the need to match this to meeting liabilities may not be receiving enough attention. What really matters is the quality of net-of-fee outcome.

The cheapening of factors ultimately destroys the active–passive distinction. That is, we think, ultimately, a good thing. The distinction was always fake anyway and made it harder to focus on the parts of asset management that were really worth paying for and those that were less important. It should foster greater awareness of factor risk and portfolio construction. It also may force a closer link from asset management to the ultimate underlying benchmarks that end-investors face.

1.10. Bibliography

[AMI 13] AMIHUD Y., GOYENKO R., "Mutual fund's R^2 as a predictor of performance", *Review of Financial Studies*, vol. 26, no. 3, 2013.

[BLA 14] BLANQUÉ P., "Essays in positive fund management", *Economica*, p. 85, 2014.

[JEN 14] JENKINSON T., JONES H., MARTINEZ J., "Picking winners? Investment consultants' recommendations of fund managers", *Journal of Finance*, vol. 71, pp. 2333–2370, 2014.

[MON 13] MONTIER J., "No silver bullets in investing (just old snake oil in new bottles)", *Journal of Index Investing*, vol. 5, pp. 77–96, 2013.

[SAP 13] SAPRA S., HUNJAN M., "Active share, tracking error and manager style", available at: http://www.pimco.co.uk/EN/Insights/Pages/Active-Share-Tracking-Error-and-Manager-Style aspx, 2013.

2

Factor Investing: The Rocky Road from Long-Only to Long-Short*

This chapter examines how restrictions on short positions affect the financial attractiveness of factor investing. To fill the gap between unconstrained long-short allocations and restricted long-only portfolios, we consider two in-between strategies. The first imposes that only the market can be shorted; the second is the so-called “130/30” or “active extension” trading strategy, which caps total short exposure at 30%. The takeaways from our research are twofold. First, short sales contribute significantly to the mean-variance performance of efficient factor-based portfolios. Second, the factor portfolios built originally by Fama and French [FAM 92] with the purpose of developing asset pricing are impressively clear-sighted when it comes to portfolio management. Indeed, combining these portfolios generates mean-variance performances similar to those of optimized long-short portfolios, except for low levels of volatility.

2.1. Introduction

Factor investing has emerged from the asset management world as the new paradigm for long-term investment [CAZ 14, JUR 15]. It attracted fresh interest after the publication of a report on active portfolio management, produced by Ang *et al*. [ANG 09] at the request of the Norwegian sovereign wealth fund. The first risk factor to be identified is the market factor, which delivers the so-called market premium. According to the capital asset pricing model (CAPM), the market premium is the only risk premium available to investors. However, a host of empirical work has uncovered additional factors that entail significant risk premia. The best-known of these relate to growth and value [FAM 92] and momentum [CAR 97]. Factor investing exhibits a

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remarkable propensity to beat the market in terms of enhancing expected returns a given level of volatility. According to Israel and Moskowitz [ISR 13] and Asness *et al.* [ASN 14], both the long and short legs of factors contribute to overall financial performance[1]. Brière and Szafarz [BRI 16] compare optimal portfolios made up of either the 10 sector indexes in the Standard Industrial Classification system, or the five long legs plus the five short legs of the factors proposed by Fama and French [FAM 15]. The results of that comparison suggest that the dominance of factor investing over sector investing relies on the possibility to make short sales. However, sizeable literature on portfolio management suggests that shorting regularly to rebalance portfolios is difficult. The aim of this paper is to assess the actual dependence of the mean-variance performances of factor investing on short-selling restrictions.

Proponents of long-short investment strategies (e.g. [MIL 01]) stress that bans on short-selling deprive investors of transaction opportunities in overvalued stocks. We therefore refrain from using a strictly binary framework: a shorting ban versus unlimited shorting. Instead, we emphasize intermediate scenarios, which are in line with the practice of US and foreign mutual funds. We consider two types of intermediate situation: the 130/30, or active extension trading strategy, and the situation where only the market can be shorted. By definition, an asset allocation strategy obeys the 130/30 rule if the total short position at any point in time is below 30% of the portfolio value, which automatically puts a 130% ceiling on the long position. While the 130/30 rule is routinely applied in fund and index management,[2] it is not commonly associated with factor investing[3]. In contrast, portfolios where only the market can be shorted are easy to implement by combining long-only portfolios with index derivatives or exchange traded funds (ETFs). This chapter will investigate both the 130/30 rule and the combination of long-only factor and long-short market investing as two strategies that are midway between the two polar cases: long-only for all assets and unrestricted long-short.

In terms of portfolio composition, the long-short factors proposed originally by Fama and French for asset pricing, such as the "small-minus-big" (SMB) size factor, can be viewed as obeying an implicit 200/100 rule that combines the market (100%) with a 100% exposure in the long leg ("small") and a 100% short position in the short leg ("big")[4]. While total exclusion of short sales is too restrictive for some investors, unlimited short-selling is mostly unrealistic. In particular, claiming that a 100% short position in factors is easily feasible is an overstatement, because factors are not directly

1 However, Blitz *et al.* [BLI 14] show that, when transaction costs and strategy capacity are factored in, long-only factors are preferable to long-short ones.
2 MSCI produces 130/30 factor indices. (https://www.msci.com/eqb/methodology/meth_docs/MSCI_Factor_Index_Methodology_May12.pdf), and fund providers supply 130/30 strategies (https://personal.vanguard.com/pdf/icrloc.pdf).
3 The paper by Lo and Patel [LO 08] is the exception.
4 The relative share of short legs in optimal factor-based portfolios often surpasses the 100% threshold (see section 2.3).

accessible to investors [IDZ 13], and factor-based ETFs typically offer exposure to long legs only. Therefore, we argue that judging the effectiveness of factor investing should take into account market characteristics such as the existence of legal restrictions and specific costs, which can significantly affect performance.

The empirical results suggest that (i) any departure from the long-short strategy harms the mean-variance performances of factor-based portfolios, and (ii) the performances of the factor portfolios that Fama and French [FAM 92] built for asset pricing purposes are remarkably similar to those of optimized long-short portfolios, except for low levels of volatility.

2.2. Short-selling and factor investing

Scholars who develop portfolio management theory and conduct empirical studies typically consider either the unconstrained situation where short-selling is unrestricted or the fully constrained situation where short sales are banned. The reasons for excluding short-selling pertain both to legal barriers and to cost issues. First, some countries forbid short sales, which can be executed only off-exchange or offshore. In a comprehensive international comparison of short-selling restrictions, Bris *et al*. [BRI 07] show that 35 countries (out of 47) permit the practice, but their tolerance is often coupled with temporary restrictions during specific periods, such as the 2007–2008 subprime crisis [BER 14]. In the United States, Regulation T governs funds' cash accounts and the amount of credit that securities brokers and dealers may extend to their clients for the purchase of securities. It limits gross exposure (the total long position plus absolute value of total short position) to no more than twice the investment capital, and so caps short sales at 50% of the portfolio. In addition, many market participants do not take full advantage of legal tolerance for shorting, mostly because these sales typically require the borrowing of securities. For instance, US mutual funds are forbidden to borrow money "unless authorized by the vote of a majority of its outstanding Voting Securities" (US Investment Company Act, Section 13(a)). Short positions are more easily obtained through derivative contracts, such as total return swaps or contracts for difference. Europe's UCITS mutual funds are prohibited from taking physical short positions, and their borrowing is limited to 10% of net assets, and for temporary purposes only. However, leverage can be generated through the use of derivatives and repos[5]. In

5 Under current UCITS regulation, funds' global leverage exposure can be measured in two different ways and the leverage constraints depend on the chosen methodology. In the commitment approach, which is appropriate for funds that do not use complex derivatives, the absolute values of the underlying exposures of the derivatives are aggregated to measure the fund's total leverage, which is restricted to 100% of the net asset value. A UCITS fund may alternatively choose to measure leverage based on a Value at Risk (VaR) approach. The

addition to regulatory constraints, restrictions can originate from funds' investment policies. Almazan *et al*. [ALM 04] find that 30% of a large sample of US equity mutual funds has the option to sell short, but only 3% actually do so.

Second, covered and uncovered short sales entail specific costs and risks. Covered (or traditional) short-selling involves borrowing the security and returning it to the lender at a given future date. The securities lending market is decentralized, so finding a lender can involve a costly search. Short-selling also exposes the trader to the risk of liquidity shortage and short squeezing [JON 02]. By contrast, uncovered short-selling is carried out without borrowing. Under US rules, the seller has three days to deliver the security to the buyer. Past this deadline, the sale can be considered as "manipulative", putting the trader at risk of legal action.

In sum, short-selling is both limited by law and costlier than regular stock purchases and sales. However, the typical factor-investing strategies rely heavily on short sales, and the bulk of the empirical literature on risk factors disregards the additional constraints associated with shorting. Factor indices rebalance individual stocks according to characteristics that change constantly. In fact, the extent of the changes varies with the type of factor. Factors such as value, size, profitability and investment are defined by means of stock characteristics with little variability, while momentum stocks change frequently. The rebalancing frequency adopted by Fama and French is yearly for the first group of factors (end-June) but monthly for the momentum portfolios. Considering a one-sided turnover resulting from averaging the values of purchased or sold assets, Novy-Marx and Velikov [NOV 16] estimate that the turnover of the size and value long-short portfolios is around 2% per year and the associated transaction costs[6] are close to 5 bps per month, regardless of the size of the portfolio. For the momentum factor, the authors find a turnover of 25% per year and transaction costs of 50 bps per month. Asness *et al*. [ASN 15] and Harvey and Liu [HAR 15] argue that the return of the high-minus-low (HML) factor might be overstated because the strategy involves shorting very small stocks. Although the transaction costs of both the conservative-minus-aggressive (CMA) investment factor and the robust-minus-weak (RMW) profitability factor are still unexplored, we conjecture that their turnover is close to that of their size and value counterparts, which are also rebalanced on a yearly basis[7]. In addition, sophisticated transaction-cost models consider the break-even capacity of each investment strategy in terms of portfolio size. By definition, break-even capacity is reached when the transaction costs are equal to the gross returns of the strategy. Using data

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absolute VaR limit depends on the risk profile of a fund, but the absolute maximum is 20% over a 20-day horizon for a confidence interval of 99%.

6 The authors estimate round-trip transaction costs related to bid-ask spreads, but do not account for the price impact of large trades (costs related to the change in price due to the trade).

7 At the portfolio level, transaction costs raise additional difficulties as purchases and sales of stocks can net out. See also [ISR 13] and [ANG 17].

on real-life trades, Frazzini *et al*. [FRA 14] estimate that the break-even capacities of the Fama and French long-short size, value and momentum factors are USD 103 billion, USD 83 billion, and USD 52 billion, respectively. These figures far exceed those computed by Lesmond *et al*. [LES 04] and Korajczyk and Sadka [KOR 04], who all rely on simple microstructure models. Still, accounting for the real costs of short-selling is well beyond the scope of this chapter. Here, we acknowledge the relevance of the problem by considering investment strategies that rely relatively little on short-selling.

Despite cost issues, the performative contributions of short positions to portfolio diversification are often mentioned. According to Jacobs and Levy [JAC 93b] and Miller [MIL 01], replacing an optimal long-short portfolio by its long-only proxy[8] can entail a significant loss of efficiency[9]. For instance, the biases in financial analysts' recommendations, materialized by the imbalance between Buy and Sell, might represent a source of profit to those who can afford to take short positions. Excluding *ex ante* any short position can thus prove detrimental to investors. To relax the constraint, middle-of-the-road options, such as the 130/30 investment rules, are proposed in the literature. Lo and Patel [LO 08, p. 12] attribute the impressive growth of the 130/30 class of strategies to "both (…) the historical success of long-short equity hedge funds and the increasing frustration of portfolio managers at the apparent impact of long-only constraints on performance". An alternative, cost-conscious option consists of restricting short-selling to assets that are liquid enough so that the position is easy to reverse if needed, thus limiting the consequences of a short squeeze. This is why we also consider an investment option where factors are long-only but the market can still be shorted.

Our portfolios of interest are made up of the market index and the five historical factors for which data are available on French's website: size (SMB), value (HML), profitability (RMW), investment (CMA) and momentum (MOM). By nature, these factors require short positions since each of them combines opposite positions on the two legs of the long-short position (e.g. "small" for the long leg, and "big" for the short leg). Thus, when it comes to investing in these factors, heavy dependence on short sales seems unavoidable. Investors may see this as a burden since factor investing is regarded as a long-term asset management strategy[10], and constant

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8 In a long-only investment universe, the second-best strategy is to underweight the assets otherwise shorted [MIC 93].

9 This statement concerns portfolios composed of any type of assets. Yet for factor-based portfolios, Israel and Moskowitz [ISR 13] show that the loss of efficiency can be less severe than expected since the long legs of factor styles typically generate over 50% of total performance. Blitz *et al*. [BLI 14] underline that, on a net basis, long-short strategies do not necessarily dominate long-only ones.

10 Ang [ANG 14] argues that factor investing is especially relevant in a long-term perspective because it takes into account the occurrence of bad times.

rebalancing is especially costly when short-selling is involved. With this in mind, those same investors might wonder how costly it would be (in terms of investment performance) to adapt the factor analysis to situations where short-selling is fully or partly restricted. Our chapter addresses this concern.

To relax the necessity of short-selling in factor investing, we proceed in two steps. First, we disentangle the long and short legs of the five historical factors. Ten resulting long-only factors provide additional flexibility in portfolio management. Second, short-selling restrictions, if any, are imposed separately on each of these 10 factors. Last, we consider separately any short-selling restrictions on the market index to show that shorting the market is much easier to do (through derivative markets, for instance) than shorting any other factor. This exploratory strategy allows us to highlight the trade-off between limiting short sales and enlarging the set possible combinations of assets. We use as a benchmark the efficient frontier composed of portfolios that combine the market index with optimized proportions of the five historical long-short factors taken from Fama and French [FAM 15], which we call the FF frontier[11], and assess alternative investment rules, including the 130/30 option, with respect to this benchmark. Our derivations follow the line of logic proposed by Clark *et al*. [CLA 04] and Sorensen *et al*. [SOR 07], who examine the consequences of imposing various realistic restrictions to portfolios, including short-selling limitations. Section 2.3 explains how we proceed in more detail.

2.3. Data and methods

2.3.1. *Data*

We use the five long-short risk factors proposed by Fama and French [FAM 92, FAM 15] and Carhart [CAR 97]: size, value, profitability, investment and momentum. From the monthly data retrieved from Ken French's website[12], covering the period stretching from July 1963 to December 2015, we constructed the long and short legs of each factor separately (see [BRI 16, for technical details). Working with classic factors (size, value and momentum) is an advantage, since the literature is consensual about their relevance [ASN 13]. The two additional factors – profitability and investment – are more controversial [HAR 16], but they allow us to take into account stock characteristics otherwise missed [NOV 13, HOU 15].

11 Accordingly, we qualify as "FF" any portfolio on this frontier.

12 http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. The investment universe considered by Fama and French is made up of stocks with a CRSP share code and positive book equity data. Moreover, the data for year t are restricted to stocks for which market prices are available in June of year t and in December of year $t-1$.

The database is composed of historic series of returns for the 10 long-only factors: (1) small, (2) big, (3) value, (4) growth, (5) robust profitability, (6) weak profitability, (7) conservative investment, (8) aggressive investment, (9) high momentum and (10) low momentum. In an optimized portfolio composition, we will let each leg have its specific exposure. Evidently, this optimization goes beyond Fama and French's original approach, which imposes opposite exposures on the two legs of the long-short position (e.g. small minus big). Still, we consider the five historical factors as a benchmark in our analysis. Overall, we are dealing with 11 elementary styles (or factors): five short legs, five long legs and the market. In unrestricted portfolios, each of these styles can be held long or short. By contrast, several types of short-selling limitations will be placed on restricted portfolios. Section 2.3.2 clarifies these limitations.

Tables 2.1 and 2.2 provide descriptive statistics and historical correlations, respectively. The factor annualized returns reported in Table 2.1 range from 7.95% (low momentum) to 16.43% (high momentum). Volatilities lie between 15.00% (big) and 21.63% (low momentum). Skewness is negative for all factors, except low momentum. Kurtosis ranges from 4.71 (growth) to 6.44 (value). Sharpe ratios are between 0.37 (low momentum) and 0.89 (high momentum). Table 2.2 presents pairwise factor correlations as well as correlations between factors and the market. Correlations between factors are homogeneously high, ranging from 0.74 (between low and high momentum) and 0.99 (between growth and aggressive investment). Unsurprisingly, the highest correlation with the market (0.99) is found for the "big" factor, composed of the large capitalizations, which drive the market index. The lowest correlation (0.87) corresponds to the low momentum factor, which picks underperforming stocks.

	Market	Small	Big	Value	Growth	Robust profitab	Weak profitab	Conservative invest	Aggressive invest	High mom	Low mom
Mean (%)	0.90	1.18	0.92	1.22	0.89	1.14	0.89	1.19	0.89	1.37	0.66
Ann. mean (%)	10.78	14.17	11.08	14.63	10.72	13.63	10.66	14.29	10.67	16.43	7.95
Median (%)	1.23	1.59	1.26	2.00	1.00	1.41	1.30	1.47	1.23	1.85	0.55
Maximum (%)	16.61	27.12	16.66	26.00	18.00	20.26	21.21	20.21	21.08	17.49	40.13
Minimum (%)	–22.64	–29.55	–21.41	–24.00	–28.00	–25.80	–27.49	–25.54	–27.82	–27.87	–24.77
Std. dev. (%)	4.43	5.81	4.33	4.90	5.48	4.91	5.53	4.93	5.62	5.32	6.24
Volatility (%)	15.35	20.12	15.00	16.97	18.97	17.00	19.17	17.07	19.48	18.42	21.63
Skewness	–0.50	–0.45	–0.42	–0.46	–0.46	–0.55	–0.48	–0.52	–0.50	–0.62	0.39
Kurtosis	4.94	5.46	4.89	6.44	4.71	5.36	4.91	5.23	4.75	5.28	7.08
Sharpe ratio	0.70	0.70	0.74	0.86	0.57	0.80	0.56	0.84	0.55	0.89	0.37

Table 2.1. *Descriptive statistics, July 1963–December 2015*

	Small	Big	Value	Growth	Robust profitab	Weak profitab	Conservative invest	Aggressive invest	High mom	Low mom
Market	0.89	0.99	0.89	0.95	0.96	0.93	0.94	0.96	0.92	0.87
Small		0.86	0.93	0.95	0.95	0.96	0.96	0.95	0.93	0.88
Big			0.90	0.92	0.95	0.91	0.92	0.93	0.89	0.86
Value				0.85	0.92	0.91	0.95	0.88	0.86	0.87
Growth					0.96	0.96	0.93	0.99	0.94	0.86
Robust profitab						0.92	0.95	0.97	0.94	0.88
Weak profitab							0.97	0.96	0.93	0.89
Conservative invest								0.94	0.92	0.88
Aggressive invest									0.94	0.88
High mom										0.74

Table 2.2. *Correlations, factors and the market, July 1963–December 2015*

2.3.2. *Methods*

In our universe of 11 elementary styles, each portfolio is defined by its vector of shares invested in each style i: $W = (w_i),\ i = 0, \ldots, 10$, with:

$$\sum_{i=0}^{11} w_i = 1 \qquad [2.1]$$

For simplicity, we number the styles as follows: the market is style 0, the long legs have odd indices (1 = small, 3 = value, 5 = conservative investment, 7 = robust profitability, 9 = high momentum) and the (positive exposures to) short legs have even indices: (2 = big, 4 = growth, 6 = aggressive investment, 8 = weak profitability, 10 = low momentum). In addition, we add up the long and short exposures to compute the global short position of portfolio W:

$$GSP(W) = \sum_{i \in \{0,1,\ldots,10\}: x_i < 0} |w_i| \qquad [2.2]$$

Hence, mimicking the typical structure of the Fama and French (FF) long-short factors (SMB, HML, CMA, RMW, and MOM) is easily done by imposing the constraint $w_i = -w_{i+1}$, for the odd values of index i. Adding to that condition the restriction of a unitary exposure to the market, we obtain the constraints fulfilled by any FF portfolio:

$$w_0 = 1 \text{ and } \forall i \in \{1,3,5,7,9\}: w_i = -w_{i+1}. \qquad [2.3]$$

Under the constraints in equation [2.3], equation [2.1] implies that $\sum_{i=1}^{11} w_i = 0$, which leaves $GSP(W)$ unrestricted. The only FF portfolio excluding short sales is the market (with $w_i = -w_{i+1} = 0,\ i > 0$). As soon as an FF portfolio has factors in its composition, it is leveraged and $GSP(X) > 0$. The total share of short positions is then: $GSP(W) = \sum_{i\in\{1,3,5,7,9\}}|w_i| = \sum_{i\in\{2,4,6,8,10\}}|w_i|$, but there is nothing to prevent a short position in a long leg or a long position in a short leg (if so, both cases occur together necessarily). The higher $GSP(W)$, the farther the FF portfolio from the market composition.

Using the efficient frontier built from the FF portfolios described in equation [2.3] as a benchmark, we examine the consequences on mean-variance performances of imposing five sets of short-selling-based restrictions in the w_i's. Table 2.1 presents the four groups of portfolios of interest according to both market exposure and the maximal admissible short-selling level. Portfolios in Group 1 (global long-only) exclude any short position whatsoever. Group 2 (long-short market + long-only factors) puts no restriction on market exposure but excludes short positions in factors. The rationale is that easy access to index trading makes shorting the market easier and less costly than shorting factors, which are hardly tradable. Group 3 includes the typical 130/30 portfolios defined by the combination of a 130% long position and a 30% short one. Finally, in Group 4, no position is constrained.

Characteristics \ Portfolios	FF benchmark portfolios	(1) Global long-only	(2) Long-short market + long-only factors	(3) 130/30	(4) Global long-short
Exposure to market	$w_0 = 1$	$w_0 > 0$	Unconstrained	$GSP(W) \leq 0.3$	Unconstrained
Exposures to styles	$w_i = -w_{i+1}$, for i odd	$w_i > 0$, for $i > 0$	$w_i > 0$, for $i > 0$		Unconstrained

Table 2.3. *Portfolios of interest*

In each group of portfolios described in Table 2.3, we perform mean-variance optimization and subsequently draw the corresponding efficient frontier, i.e. the curve representing the optimized portfolios in the mean-variance plane. To assess the performance of these efficient frontiers, we define three benchmark portfolios on the FF frontier (see equation [2.3]) by means of their volatilities. First, the FF minimum-variance portfolio (*FFminvol*) has a volatility of 13.37%. Second, the FF market-volatility portfolio (*FFmktvol*) has a volatility of 15.35%. Last, we consider an FF portfolio with high volatility (*FFhighvol*). This portfolio is defined as the one that makes the volatility of the market equidistant from those of *FFminvol* and *FFhighvol*. The benchmark high volatility is thus equal to: 15.35% + (15.35% – 13.37%) = 17.33%. Table 2.4 gives the composition of the three benchmark portfolios. As expected, the magnitude of the short exposure increases with the level of volatility.

	FFminvol	FFmktvol	FFhighvol
Ann. return (%)	15.06	22.91	26.54
Volatility (%)	13.37	15.35	17.33
Composition			
Market	1	1	1
Small	–0.25	0.16	0.35
Big	0.25	–0.16	–0.35
Value	0.04	0.13	0.18
Growth	–0.04	–0.13	–0.18
Robust profitab	0.34	0.93	1.21
Weak profitab	–0.34	–0.93	–1.21
Conservative invest	0.8	1.37	1.64
Aggressive invest	–0.8	–1.37	–1.64
High mom	0.12	0.39	0.52
Low mom	–0.12	–0.39	–0.52
Total share of long positions	2.54	3.99	4.90
Total share of short positions	–1.54	–2.99	–3.90

Table 2.4. *The benchmark portfolios*

In line with the logic underlying the FF factors, optimization puts positive weights on long legs and negative ones on short legs in all cases but one: in the *FFminvol* portfolio, the long leg of the size factor has a negative coefficient (–0.25), which automatically imposes the symmetrical long position in the short leg. The total share of long positions in the portfolio, $\sum_{i\in\{1,3,5,7,9\}} w_i$, increases with portfolio volatility, as do the individual shares of each long leg. By contrast, the coefficient of the market is set at 100%, meaning that the role of the market decreases when the FF portfolio becomes more volatile. The increase is particularly impressive for the coefficient of the profitability factor, which goes from 0.34 for *FFminvol* to 0.94 for *FFmktvol*, and to 1.51 for *FFhighvol*. Likewise, the loading on conservative investment is almost double that on the market (193% versus 100%). Profitability and investment are the two most recent factors [FAM 15], suggesting that the risk premia associated with factors, sometimes referred to as anomalies, tend to erode after their discovery [MCL 16]. While Table 2.1 indicates that the market annualized return over the period is 10.78%, the same-volatility FF portfolio, *FFmktvol*, reaches more than twice that figure (22.9%). Overall, the mean-variance performances of the three benchmark portfolios are remarkable, meaning that we set the bar fairly high.

We assess the financial performances of the efficient frontiers corresponding to the four groups of portfolios in Table 2.3 by comparing these frontiers to the benchmark FF portfolios by means of geometric tests. In fact, the common procedure here would have consisted of using spanning tests, but these are applicable to unconstrained portfolios only [WAN 98]. By contrast, the geometric tests work well when constraints on the coefficients are imposed. More precisely, our assessment tools are based on distance computations in the mean-variance plan. The Basak *et al.* [BAS 02] test, respectively the Brière *et al.* [BRI 13] test, exploits the horizontal, respectively vertical, distance between a given portfolio and an efficient frontier[13]. In both cases, if the returns on the assets are jointly normal, under the null that distance is zero, the test statistics has an asymptotic normal distribution. The two tests complement one other usefully, as it may happen (and will happen in our analysis) that neither test is applicable because of the shape of the efficient frontier of interest. Intuitively, the null that the horizontal, respectively vertical, distance is zero means that the portfolios optimized within the given asset group match the volatility, respectively expected return, performances of the benchmark portfolio. By contrast, a significantly positive outperformance indicates that the group of portfolios in question performs better than the benchmark, while a negative score signals an underperformance. Better performance means higher returns for the horizontal distance, and lower volatility for the vertical one.

Practically, we will apply both tests to each pair made up of one benchmark portfolio and the efficient frontier corresponding to one of the four cases described in Table 2.3. So, we will end up with (at most) six test results (two distances applied with respect to three benchmark portfolios) for every asset allocation scenario, the numerical results being supported by the graphical visualization of efficient

13 More complex distances combining the two dimensions exist in the literature [BRI 04], but corresponding tests have not been developed yet.

frontiers. The overall objective of the exercise is twofold. First, we seek a global picture of the impact on portfolio performance of short-selling constraints with variable degrees of severity. Second, a more detailed analysis will investigate whether the performance losses resulting from restrictions on short-selling are mediated by portfolio volatility, a parameter driven chiefly by the investor's risk aversion. If so, the practical consequences of short-selling limitations would not affect all investors equally. Intuitively, one expects that a lower level of risk aversion makes an investor keener to go short and hence more sensitive to short-selling restrictions. The empirical results in section 2.4 will check the relevance of this intuition.

2.4. Empirical results

2.4.1. *Efficient frontiers*

Consistent with Table 2.3, we start by representing the five efficient frontiers of interest, namely the benchmark FF frontier as well as the frontier associated with the four groups of portfolios to be tested. From definitions, we expect that the frontier corresponding to the global long-short case (Group 4) dominates all the others, including the benchmark, since it allows fully unconstrained optimization. Likewise, the global long-only case (Group 1) is evidently more restrictive than both the cases of the long-short market + long-only factors (Group 2) and the 130/30 (Group 3). This implies that the frontier associated with Group 1 must be dominated by the other two. There is no clear dominance to be expected between the frontiers corresponding to Groups 2 and 3, since, on the one hand, the exposure to the market is unconstrained in Group 2 but constrained by the 130/30 restriction in Group 3, and the other factors can be shorted (to a certain extent) in Group 3 but not at all in Group 2. Hence, comparing the frontiers obtained for Groups 2 and 3 can bring insights into the trade-off arising from shorting the market only versus shorting single-legged factors. Given the specific constraints used to define the benchmark FF portfolios (see equation [2.3]), we have no priors on how the FF efficient frontier is located with respect to the efficient frontiers for Groups 1–3.

Figure 2.1 shows our five efficient frontiers. It reveals that the expected dominances are observed graphically. It also shows that the frontiers associated with Groups 2 and 3 do eventually intersect, and the intersection point has a relatively high volatility level of between 16% and 17%. One possible interpretation is that shorting the market is useful for decreasing the overall volatility of the portfolio, while shorting factors allows investors with low risk aversion to benefit from leverage effects that drive both higher volatility and higher expected returns.

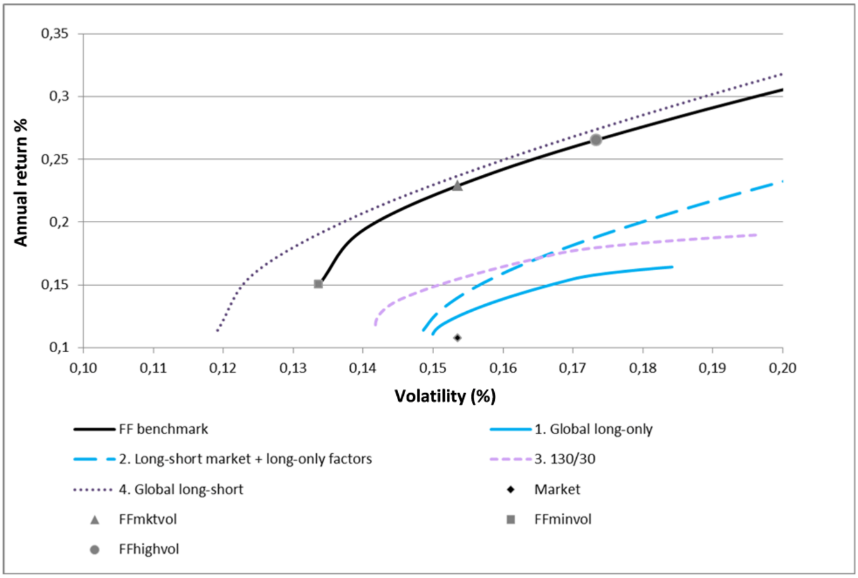

Figure 2.1. *Efficient frontiers. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

Remarkably, the benchmark FF frontier seems to largely dominate the efficient frontiers derived for cases 1–3, while there is no theoretical argument supporting these facts. Another, and perhaps more disturbing piece of evidence as far as theory is concerned, relates to the position of the market portfolio on Figure 2.1. It is located below all our frontiers of interest, even the most restricted one (corresponding to Group 1), which bans any short sale. This could be viewed as contradicting the CAPM, which predicts that the market portfolio is efficient. Admittedly, from a statistical standpoint, the distance between the point representing the market portfolio and the Group 1 frontier can be (and probably is) insignificant. The formal tests in section 2.4.2 will show that the results go in the opposite direction when the benchmark frontier is considered.

2.4.2. *Horizontal and vertical tests*

Tables 2.5–2.8 show the test results for the four groups of portfolios described in Table 2.1 and for which Figure 2.1 gives the efficient frontiers. In each table, a given group is tested by means of the Basak *et al.* [BAS 02] horizontal test and the Brière *et al.* [BRI 13] vertical test, both of which exploit distances in the mean-variance plan. Each test is run for three FF benchmark portfolios, namely *FFmktvol* that has market volatility, and the two portfolios symmetrically located on its left, *FFminvol*, and on its right, *FFhighvol*. Empty columns show that the tests are sometimes unfeasible because efficient frontiers may lack a portfolio with same expected return (for the horizontal test) or same volatility (for the vertical test) as a given benchmark portfolio. This problem shows up more frequently for frontiers that are relatively farther away from the FF benchmark frontier.

Efficient frontier for Group 1	Excess return (horizontal test)			Excess variance (vertical test)		
Benchmark portfolio	FFminvol	FFmktvol	FFhighvol	FFminvol	FFmktvol	FFhighvol
Outperformance (expected return/variance)	–0.0008***	–	–	–	–0.0086***	–0.0089***
Composition of the efficient portfolio with same variance/expected return as the benchmark						
Small	0.00	–	–	–	0.00	0.00
Big	0.09	–	–	–	0.64	0.00
Value	0.52	–	–	–	0.29	0.37
Growth	0.00	–	–	–	0.00	0.00
Robust profitab	0.00	–	–	–	0.00	0.00
Weak profitab	0.00	–	–	–	0.00	0.00
Conservative invest	0.00	–	–	–	0.00	0.00
Aggressive invest	0.00	–	–	–	0.00	0.00
High mom	0.39	–	–	–	0.06	0.63
Low mom	0.00	–	–	–	0.00	0.00
Market	0.00	–	–	–	0.00	0.00
Total share of long positions	1.00	–	–	–	1.00	1.00
Total share of short positions	0.00	–	–	–	0.00	0.00

Table 2.5. *Test results for Group 1: global long-only*

Preliminary examination of Tables 2.5–2.7 reveals that all the tests run for Groups 1–3 exhibit underperformances (negative outperformances) that are significant at the 1% level, suggesting that the portfolios in the three groups fail to reach the performances of the FF benchmarks, in terms of expected returns as well as volatility. Consequently, the flexibility gained by disconnecting the weights of the long and short factor legs does very little to offset the performance advantages associated with the high levels of short positions in the FF portfolios. Even partially relaxing the short-selling restrictions in two different ways (on the market index only in Group 2, and by allowing 30% or less of short sales in Group 3) is largely insufficient to effectively challenge the performances of FF benchmark portfolios.

Efficient frontier for Group 2	Excess return (horizontal test)			Excess variance (vertical test)		
Benchmark portfolio	FFminvol	FFmktvol	FFhighvol	FFminvol	FFmktvol	FFhighvol
Outperformance (expected return/variance)	–0.0005***	–0.0012***	–0.0016***	–	–0.0074***	–0.0064***
Composition of the efficient portfolio with same variance/expected return as the benchmark						
Small	0.00	0.00	0.00	–	0.00	0.00
Big	3.59	6.57	7.92	–	3.15	5.04
Value	0.02	0.00	0.00	–	0.04	0.00
Growth	0.00	0.00	0.00	–	0.00	0.00
Robust profitab	0.00	0.32	0.52	–	0.00	0.08
Weak profitab	0.00	0.00	0.00	–	0.00	0.00
Conservative invest	0.04	0.21	0.26	–	0.00	0.15
Aggressive invest	0.00	0.00	0.00	–	0.00	0.00
High mom	0.52	1.51	1.95	–	0.37	1.02
Low mom	0.00	0.00	0.00	–	0.00	0.00
Market	–3.18	–7.61	–9.65	–	–2.57	–5.30
Total share of long positions	4.18	8.61	10.65	–	3.57	6.30
Total share of short positions	–3.18	–7.61	–9.65	–	–2.57	–5.30

Table 2.6. *Test results for Group 2: long-short market + long-only factors*

The compositions of the efficient portfolios used in the comparisons with benchmark portfolios are visible in the lower part of each table (Tables 2.5–2.8). In Table 2.5, where short positions are forbidden, the reported compositions exclude, surprisingly, the “small” leg of the traditional size factor, as well as both legs of the newer factors, “profitability” and “investment”. These compositions are dominated by the “value” and “high momentum” factors, with a special role for “big” in the portfolio with the same expected return as the *FFmktvol*, probably because the market and the “big” leg of SMB are strongly correlated. The market itself is absent from the compositions. By contrast, Table 2.6 reports impressive short positions in the market index (between 257% and 965%). Since this index is the only style that can be shorted in the Group 2 configuration, these compositions, which are heavily loaded in short sales, indirectly illustrate just how binding the short-selling restrictions are. This is especially relevant given that the compositions reported in Table 2.7 for 130/30 portfolios allocate zero coefficients to the market. One interpretation could be that the 30% authorized share of short-selling is too precious to be dedicated to the market. Instead, it is fully attributed to “low momentum”, while positive coefficients are found for “big”, “value”, and “high momentum”.

Efficient frontier for Group 3	Excess return (horizontal test)			Excess variance (vertical test)		
Benchmark portfolio	FFminvol	FFmktvol	FFhighvol	FFminvol	FFmktvol	FFhighvol
Outperformance (expected return/variance)	–0.0004***	–	–	–	–0.0062***	–0.0071***
Composition of the efficient portfolio with same variance/expected return as the benchmark						
Small	0.00	–	–	–	0.00	0.00
Big	0.53	–	–	–	0.44	0.00
Value	0.63	–	–	–	0.67	0.59
Growth	0.00	–	–	–	0.00	0.00
Robust profitab	0.00	–	–	–	0.00	0.00
Weak profitab	0.00	–	–	–	0.00	0.00
Conservative invest	0.00	–	–	–	0.00	0.00
Aggressive invest	0.00	–	–	–	0.00	0.00
High mom	0.14	–	–	–	0.19	0.71
Low mom	–0.30	–	–	–	–0.30	–0.30
Market	0.00	–	–	–	0.00	0.00
Total share of long positions	1.30	–	–	–	1.30	1.30
Total share of short positions	–0.30	–	–	–	–0.30	–0.30

Table 2.7. *Test results for Group 3: 130/30*

In fact, short positions close to those originally imposed in the FF strategy are well designed to capture the risk premia associated with factors. Put differently, the way Fama and French built their factors for making their case in asset pricing holds up exceptionally well in the transition to portfolio management. This is an impressive accomplishment coming from a literature that, for decades, was devoted exclusively to asset pricing.

Efficient frontier for Group 4	Excess return (horizontal test)			Excess variance (vertical test)		
Benchmark portfolio	FFminvol	FFmktvol	FF17.3%vol	FFminvol	FFmktvol	FF17.3%vol
Outperformance (expected return or variance)	0.0002***	0.0001*	0.0001*	0.0033***	0.0006	0.0007
Composition of the efficient portfolio (same variance/expected return as the benchmark)						
Small	2.25	1.25	0.79	1.73	1.15	0.68
Big	–0.03	–0.47	–0.67	–0.26	–0.51	–0.71
Value	–0.23	–0.21	–0.20	–0.22	–0.21	–0.20
Growth	–0.08	–0.37	–0.50	–0.23	–0.39	–0.53
Robust profitab	–0.35	0.46	0.83	0.06	0.54	0.92
Weak profitab	–0.83	–1.13	–1.27	–0.99	–1.16	–1.30
Conservative invest	–0.57	0.44	0.91	–0.05	0.54	1.02
Aggressive invest	–2.31	–2.49	–2.57	–2.40	–2.51	–2.59
High mom	–0.12	0.98	1.49	0.45	1.09	1.61
Low mom	–0.31	0.00	0.14	–0.15	0.03	0.18
Market	3.58	2.53	2.05	3.04	2.43	1.94
Total share of long positions	5.83	5.67	6.21	5.29	5.78	6.34
Total share of short positions	–4.83	–4.67	–5.21	–4.29	–4.78	–5.34

Table 2.8. *Test results for Group 4: global long-short*

Table 2.8 contrasts with the others since it reports positive outperformance. This is in line with the fact that it reports on the performances of efficient long-short portfolios compared to those of the FF benchmarks. As Figure 2.1 shows, the two frontiers are close to one other, especially with volatility above a threshold that sits visually around 14%. Table 2.8 provides formal confirmation of this intuition. It highlights that the global long-short frontier outperforms the FF minimal volatility portfolio, *FFminvol*, both in expected return and in volatility. More generally, highly risk-averse investors prefer freely optimized long-only portfolios over factor-based portfolios built according to the standard FF rule summarized in equation [2.3]. Remarkably, however, those who tolerate medium to low levels of risk can safely avoid the inconvenience of tailoring their own portfolios and opt for the efficient FF portfolio that matches their desired level of volatility. Interestingly, Table 2.8 reveals that the total shares of short positions are high (in absolute value) along the efficient frontier, as expected, but eventually the variations prove to be modest. For instance, the benchmark *FFminvol* portfolio reaches a volatility of 13.37% with a short position of 154% (see Table 2.3), its same-variance counterpart on the Group 7 efficient frontier has a total share of short positions equal to 483%, more than three times the benchmark value. Table 2.8 proves that the impressive amount of shorting is profitable in terms of excess returns. However, for riskier portfolios, discrepancies in total short positions and the resulting outperformances are smaller and mostly insufficient to recommend the global long-short strategy over the FF benchmark.

2.5. Conclusion

The main takeaways of this chapter are twofold. First, short-selling enhances the performance of factor investing. Long-short strategies can exhibit attractive mean-variance performance. Our results contrast with those of Israel and Moskowitz [ISR 13] and Asness *et al*. [ASN 14], who instead consider investments in individual factors. This difference is probably due to the fact that we run optimal asset allocations (under a series of predefined constrained) that combine styles, which embody both the long and short legs of the FF factors. Second, the way Fama and French [FAM 92] built factor portfolios in an asset pricing perspective was impressively clear-sighted in terms of portfolio management. These two-leg optimization-free portfolios are obtained from equal absolute weights of the long and short legs. Our tests results suggest that, except for low levels of volatility, the FF portfolios generate performances which are as good as those of optimized long-short portfolios.

Our paper contributes to the debate on the efficiency gains associated with relaxing the long-only restriction on portfolio optimization [BRU 97, JAC 05, JAC 07 in the specific context of factor investing [EUN 10, ANG 14]. Legal restrictions and specific costs aside, long-short strategies are evidently superior to long-only ones because they capture investment opportunities that are otherwise inaccessible. This point has been made repeatedly in the literature, along with various performance indicators such as higher alphas and lower tracking errors [SOR 07], diversification benefits [KRU 08] and higher efficiency [JOH 07]. With respect to this literature stream, our methodological innovation arises from using intermediate situations that depart from both the highly restrictive long-only case and the (too?) permissive long-short rule.

2.6. Bibliography

[ALM 04] ALMAZAN A., BROWN K.C., CARLSON M. *et al.*, "Why constraint your mutual fund manager?", *Journal of Financial Economics*, vol. 73, pp. 289–321, 2004.

[ANG 09] ANG A., GOETZMANN W., SCHAEFER S., Evaluation of Active Management of the Norwegian GPFG, Report, Ministry of Finance, Norway, 2009.

[ANG 14] ANG A., *Asset Management – A Systematic Approach to Factor Investing*, Oxford University Press, Oxford, 2014.

[ANG 17] ANG A., RATCLIFFE R., MIRANDA P., Capacity of smart beta strategies: a transaction cost perspective, working paper, Columbia Business School Research Paper No. 16–76, 2017.

[ASN 13] ASNESS C.S., MOSKOWITZ T., PEDERSEN L., "Value and momentum everywhere", *Journal of Finance*, vol. 68, pp. 929–985, 2013.

[ASN 14] ASNESS C.S., FRAZZINI A., ISRAEL R. *et al.*, "Fact, fiction, and momentum investing", *Journal of Portfolio Management*, vol. 40, pp. 75–92, 2014.

[ASN 15] ASNESS C.S., ILMANEN A., ISRAEL R. *et al.*, "Investing with style", *Journal of Investment Management*, vol. 13, pp. 27–63, 2015.

[BAS 02] BASAK G., JAGANNATHAN R., SUN G., "A direct test for the mean-variance efficiency of a portfolio", *Journal of Economic Dynamics and Control*, vol. 26, pp. 1195–1215, 2002.

[BER 14] BERNAL O., HERINCKX A., SZAFARZ A., "Which short-selling regulation is the least damaging to market efficiency? Evidence from Europe", *International Review of Law and Economics*, vol. 37, pp. 244–256, 2014.

[BLI 14] BLITZ D., HUIJ J., LANSDORP S. *et al.*, Factor investing: long-only versus long-short, SSRN working paper No. 2417221, 2014.

[BRI 04] BRIEC W., KERSTENS K., LESOURD J., "Single-period Markowitz portfolio selection, performance gauging, and duality: a variation on the Luenberger shortage function", *Journal of Optimization Theory and Applications*, vol. 120, pp. 1–27, 2004.

[BRI 13] BRIÈRE M., DRUT B., MIGNON V. *et al.*, "Is the market portfolio efficient? A new test of mean-variance efficiency when all assets are risky", *Finance*, vol. 34, pp. 7–41, 2013.

[BRI 16] BRIÈRE M., SZAFARZ A., Factor investing: risk premia versus diversification benefits, SSRN working paper No. 2615703, 2016.

[BRI 07] BRIS A., GOETZMANN W.N., ZHU N., "Efficiency and the bear: short sales and markets around the world", *Journal of Finance*, vol. 62, pp. 1029–1079, 2007.

[BRU 97] BRUSH J.S., "Comparisons and combinations of long and long-short strategies", *Financial Analyst Journal*, vol. 53, pp. 81–89, 1997.

[CAR 97] CARHART M.M., "On persistence in mutual fund performance", *Journal of Finance*, vol. 52, pp. 57–82, 1997.

[CAZ 14] CAZALET Z., RONCALLI T., Facts and fantasies about factor investing, SSRN working paper No. 2524547, 2014.

[CLA 04] CLARKE R., DE SILVA H., SAPRA S., "Toward more information-efficient portfolios", *Journal of Portfolio Management*, vol. 31, pp. 54–63, 2004.

[EUN 10] EUN C.S., LAI S., DE ROON F.A. *et al*., "International diversification with factor funds", *Management Science*, vol. 56, pp. 1500–1518, 2010.

[FAM 92] FAMA E.F., FRENCH K.R., "The cross-section of expected stock returns", *Journal of Finance*, vol. 47, pp. 427–465, 1992.

[FAM 15] FAMA E.F., FRENCH K.R., "A five-factor asset pricing model", *Journal of Financial Economics*, vol. 116, pp. 1–22, 2015.

[FRA 14] FRAZZINI A., ISRAEL R., MOSKOWITZ T., Trading costs of asset pricing anomalies, Fama-Miller working paper, Chicago Booth Research Paper No. 14-05, 2014.

[GIL 11] GILLI M., SCHUMANN E., DI TOLLO G. *et al*., "Constructing 130/30-portfolios with the omega ratio", *Journal of Asset Management,* vol. 12, pp. 94–108, 2011.

[HAR 15] HARVEY C.R., LIU Y., "Backtesting", *Journal of Portfolio Management,* vol. 42, pp. 13–28, 2015.

[HAR 16] HARVEY C.R., LIU Y., ZHU H., "… And the cross section of expected returns", *Review of Financial Studies*, vol. 29, pp. 5–68, 2016.

[HOU 15] HOU K., XUE C., ZHANG L., "Digesting anomalies: an investment approach", *Review of Financial Studies*, vol. 28, pp. 650–705, 2015.

[IDZ 13] IDZOREK T. M., KOWARA M., "Factor-based asset allocation vs. asset-class-based asset allocation", *Financial Analyst Journal*, vol. 69, pp. 1–11, 2013.

[ISR 13] ISRAEL R., MOSKOWITZ T., "The role of shorting, firm size, and time on market anomalies", *Journal of Financial Economics*, vol. 108, pp. 275–301, 2013.

[JOB 81] JOBSON J.D., KORKIE B.M., "Performance hypothesis testing with the Sharpe and Treynor measures", *Journal of Finance*, vol. 36, pp. 889–908, 1981.

[JON 02] JONES C.M., LAMONT O.A., "Short-sale constraints and stock returns", *Journal of Financial Economics*, vol. 66, pp. 207–239, 2002.

[JAC 93] JACOBS B.I., LEVY K.N., "Long short equity investing", *Journal of Portfolio Management*, vol. 20, pp. 52–64, 1993.

[JAC 05] JACOBS B.I., LEVY K.N., MARKOWITZ H.M., "Portfolio optimization with factors, scenarios, and realistic short positions", *Operations Research,* vol. 53, pp. 586–599, 2005.

[JAC 07] JACOBS B.I., LEVY K.N., "20 Myths about enhanced active 120-20 strategies", *Financial Analysts Journal,* vol. 63, pp. 19–26, 2007.

[JOR 86] JORION P., "Bayes-Stein estimation for portfolio analysis", *Journal of Financial and Quantitative Analysis*, vol. 21, pp. 279–292, 1986.

[JUR 15] JURCZENKO E., MICHEL T., TEILETCHE J., "A unified framework for risk-based investing", *Journal of Investment Strategies*, vol. 4, pp. 1–29, 2015.

[KOR 04] KORAJCZYK R.A., SADKA R., "Are momentum profits robust to trading costs?", *Journal of Finance*, vol. 59, pp. 1039–1082, 2004.

[KRU 08] KRUSEN C., WEBER F., WEIGAND R.A., "130/30 Funds: the evolution of active equity investing", *Journal of Portfolio Management*, vol. 1, pp. 176–185, 2008.

[LED 04] LEDOIT O., WOLF M., "Honey, i shrunk the sample covariance matrix", *Journal of Portfolio Management*, vol. 30, pp. 110–119, 2004.

[LES 04] LESMOND D.A., SCHILL M.J., ZHOU C., "The illusory nature of momentum profits", *Journal of Financial Economics*, vol. 71, pp. 349–380, 2004.

[LO 08] LO A.W., PATEL P.N., "130/30: The new long-only", *Journal of Portfolio Management,* vol. 34, pp. 12–38, 2008.

[MCL 16] MCLEAN R.D., PONTIFF J., "Does academic research destroy stock return predictability?", *Journal of Finance*, vol. 71, pp. 5–32, 2016.

[MIC 93] MICHAUD R., "Are long-short equity strategies superior?", *Financial Analysts Journal*, vol. 49, pp. 44–50, 1993.

[MIL 01] MILLER E.M., "Why the low returns to beta and other forms of risk?", *Journal of Portfolio Management*, vol. 27, pp. 40–56, 2001.

[NOV 13] NOVY-MARX R., "The other side of value: the gross profitability premium", *Journal of Financial Economics*, vol. 108, pp. 1–28, 2013.

[NOV 16] NOVY-MARX R., VELIKOV M., "A taxonomy of anomalies and their trading cost", *Review of Financial Studies*, vol. 29, pp. 104–147, 2016.

[SOR 07] SORENSEN E.H., HUA R., QIAN E., "Aspects of constrained long-short equity portfolios: taking off the handcuffs", *Journal of Portfolio Management*, vol. 33, pp. 12–22, 2007.

[WAN 98] WANG Z., "Efficiency loss and constraints on portfolio holdings", *Journal of Financial Economics*, vol. 48, pp. 359–375, 1998.

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3

Peering under the Hood of Rules-Based Portfolio Construction: The Impact of Security Selection and Weighting Decisions

This chapter delves deeply into an area of rules-based portfolio construction that has largely been overlooked. We discuss the impact of screening and weighting decisions on portfolio characteristics and performance. We show how this occurs through the effect of screening and weighting decisions on the maximum effective multiplier (MEM) of a portfolio. Furthermore, we demonstrate a closed-form solution to the MEM under a certain set of conditions. Importantly, we highlight that screening and weighting decisions interact, and should therefore not be made independently. Ultimately, the performance and characteristics of a portfolio is linked to the combined effect of screening and weighting decisions through the MEM.

3.1. Introduction

Rules-based non-market cap-weighted index-based investing, also known as smart beta, advanced beta, factor investing and risk premia investing among its many names, has generated a lot of research over the past several years. As detailed in [BEN 15b] and [BEN 15a], the concept of passively managed portfolios (PMF portfolios) has been around since the 1980s. Its foundations are decades long starting with Rosenberg and Marathe [ROS 76a] and Ross [ROS 76b]. PMF investing can generally be viewed as a way for investors to capture key sources of return (factors) through a rules-based cost-efficient index. Well-known factors are those such as value, size and momentum

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but our framework here can, in theory, apply to any targeted source of return or investment theme. Bender *et al*. [BEN 13] provide a review of the foundations of factor investing.

Rules-based portfolio construction appears relatively simple at first glance but we believe this simplicity is misleading. In this chapter, our aim is to peer under the hood of rules-based portfolio construction and to shed light on the complexities that may arise from using simple rules. Our hope is to turn the spotlight on an area we feel is largely and unduly overlooked. We also hope that investors in PMF portfolios will use the takeaways here to become more critical of obvious examples of data mining.

The remainder of the paper is as follows. Section 3.2 provides a framework for rules-based portfolio construction and section 3.3 drills down into the two main portfolio construction decisions – security screening and security weighting. Section 3.4 introduces the MEM as an important metric for understanding different weighting schemes. Section 3.5 explores how screening and weighting decisions impact the MEM and through it, key portfolio characteristics. We conclude by discussing the implications of these results for constructing factor portfolios.

3.2. A framework for rules-based portfolio construction

"Smart beta" or PMF portfolios largely use rules-based or heuristic methods to determine portfolio constituents and weights. Preference for this approach over more complicated portfolio construction methods has largely been because of its appeal to investors. This is important since investors are choosing which factors to invest in, as opposed to hiring active managers to do so. If the investor does not understand how the portfolio is constructed, then the investor is less confident about owning the decision. In other words, PMF requires the portfolio construction rules to be clear and transparent, which tends to favor heuristic methods.

The first PMF strategies – equal weighting, GDP weighting and fundamental indexation – all use relatively simple portfolio construction rules. In these examples, the weights of the securities are a function of the number of stocks, the GDP of the country the security was domiciled in and the fundamental value (book value, cash flow, etc.), respectively.

A general framework for capturing these different weighting schemes is to express security weights as multipliers applied to either market cap weights or equal weights. We favor this framework because it is intuitive and links the underlying source of return to the weights in the portfolio. The weight of each security in the portfolio is written as:

$$w_i^{Tilt} = w_i^{Start} \times z_i \qquad [3.1]$$

where z_i is a multiplier applied to a starting set of security weights, e.g. market cap weight or equal weight. The scalar z_i can be specified in many ways. It can be the result of a mapping function based on the security's factor characteristics. It can be nonlinear or linear cross-sectionally, and it can be unique for individual securities or groups of securities. As discussed in [BEN 15b], fundamental-weighted indices and most other commercial indices are either explicitly constructed along these lines or can be rewritten in this way.

The intuitive appeal of this framework is that the multipliers control the degree to which we push a stock's weight above or below its starting weight. Larger multipliers can be given to the stocks that deliver more exposure to the factor. Smaller multipliers can be given to the stocks that deliver negative exposure to the factor. A multiplier of zero means the stock is not held. The framework merely translates the decision about which weights to assign to a decision about which multipliers to assign and what starting weights to use. For the remainder of the paper, we employ this framework.

3.3. Key decisions for rules-based portfolio construction: security selection and weighting

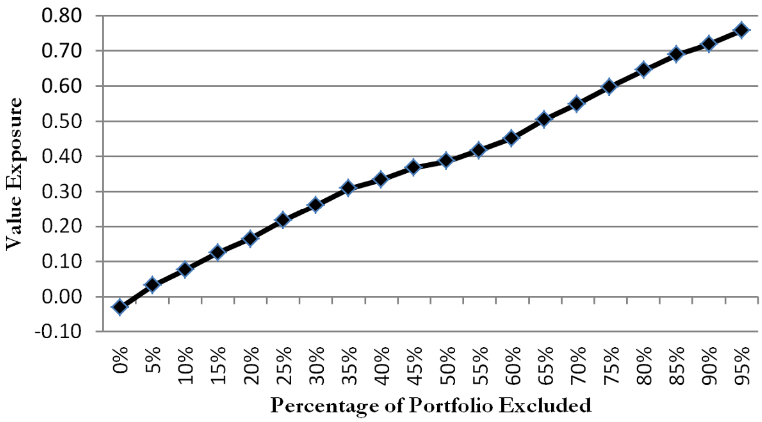
Security selection (also called stock selection or screening) and stock weighting are the two main decisions in rules-based portfolio construction. For example, in a prime example of a fundamentally weighted index, the FTSE RAFI US 1000 Index, the securities selected are the top 1,000 companies from the FTSE US All Cap Index ranked by a composite fundamental value score (a composite of book value, cash flow, sales and dividends). This is the security selection step. The weights of the securities are then set proportional to their fundamental values. This is the security weighting step.

The two decisions do not at first glance appear complicated. However, where it does get complicated is if there are specific portfolio objectives to be attained – a desired level of factor exposure, a desired level of tracking error, a desired level of turnover, maximum weights on certain sectors and countries and so forth. Both security selection and weighting can be fine-tuned to meet specific portfolio objectives. In general, the fewer securities selected as a percentage of the number of securities in the benchmark, and the more aggressive the weighting scheme (i.e. the more extreme the multipliers are), the higher the tracking error, factor exposure and active weights. But the impact of selection versus weighting is not uniform. In fact, as we will see, the only way to achieve meaningful levels of tracking error in some instances is to use aggressive levels of screening. There can be a limit to the impact of weighting.

3.3.1. *Security selection*

Building PMF portfolios usually begins with defining a universe, typically the universe of stocks in the benchmark index. Securities are selected from this universe based on criteria that reflect the underlying objective or targeted factor. The more stocks that are screened out, i.e. the fewer stocks chosen, the higher the tracking error will be. This relationship is strongly positive, in some instances monotonic. At the same time, the more stocks that are screened out, the higher the exposure to the targeted factor will generally also be, and if the return to the factor is positive, the higher the return will generally be. The relationship between exposure/return and security selection is also strongly positive.

Let us illustrate this with an example. First, we start with a global developed market large/mid cap universe of securities, the constituents of the MSCI World Index. We rank the securities once a year in March based on their value characteristics[1]. Next, we divide the securities into 20 subportfolios each containing 5% of the market cap weight of the universe. The subportfolios thus range from very cheap to very expensive. Finally, starting with the market cap weighted universe, we take one subportfolio out one at a time, starting with the most expensive, and ending with the cheapest based on valuation, so that the portfolio becomes successively more value-like. The tracking error as we do so is shown in Figure 3.1.

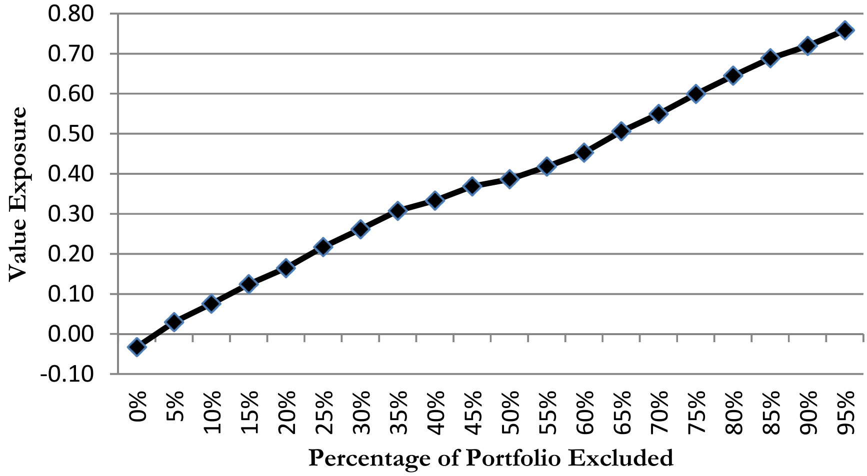


Starting universe and Benchmark is MSCI World Index.

Figure 3.1. *Tracking error increases with fewer stocks (Value Portfolio, April 1989–September 2014)*

1 Our definition of value is an equal weighted blend of five fundamentals to price. The fundamentals are book value, earnings, sales, cash flow and dividends.

What happens to exposures? As we remove subportfolios, the exposure also increases as shown in Figure 3.2 (exposures are estimated by running regressions on the Fama–French [FEM 92, FEM 93] Global 3 factors of Market, HML, SMB and momentum factor of WML).

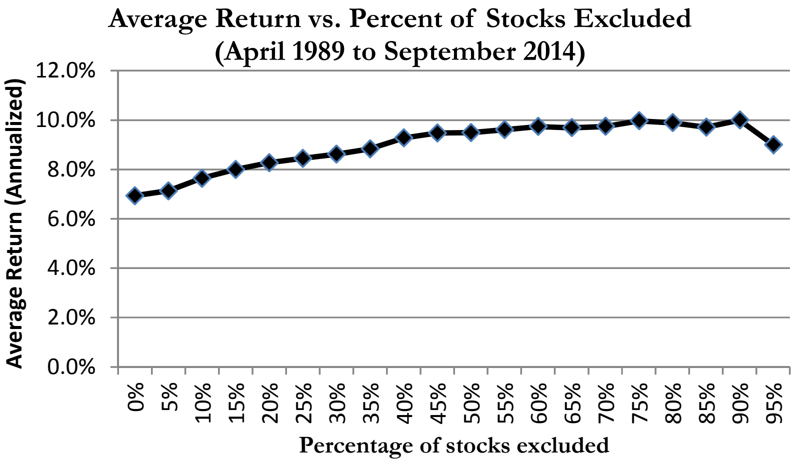


Starting universe and Benchmark is MSCI World Index.

Figure 3.2. *Factor exposure increases with fewer stocks (Value Portfolio, April 1989–September 2014)*

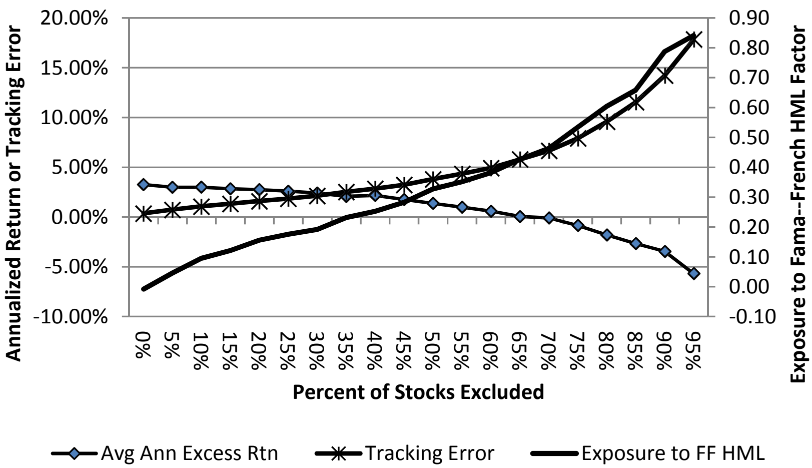
In periods in which value as a factor performed well, the realized return will also improve as we successively remove subportfolios (see Figure 3.3) but the opposite is true in periods where value performed poorly (Figure 3.4).

It is important to note that as more stocks are screened out, the stock-specific component becomes an increasingly greater driver of returns and risk. At the same time, systematic sources of risk and return become less important, including the targeted factor itself. Clearly, a PMF portfolio needs to hold enough names such that the stock-specific component does not dominate. For sufficiently high tracking error high exposure PMF portfolios, using optimization-based methods may be more suitable for controlling this proportion.



Starting universe and Benchmark is MSCI World Index.

Figure 3.3. *Average return increases with fewer stocks as long as the underlying factor performed well during that period: example with Value Portfolio (April 1989–September 2014)*



Starting universe and Benchmark is MSCI World Index.

Average Annualized Excess Return and Tracking Error are computed relative to MSCI World Index.

Figure 3.4. *More concentrated portfolios experience greater return drag when the underlying factor does poorly (Value Portfolio, June 2007–September 2014)*

For now, we assume that we have a sufficient number of names and diversification such that the factor contribution to return and risk is strong. Note for instance that even if we hold only 10% of the names of a broad index like the MSCI World Index, which contains 1,637 names as of October 31, 2016, we would still hold over 160 securities, which is sufficiently diverse.

3.3.2. *Security weighting*

The security weighting decision involves how we decide the weights of the securities we selected. Similar to the security selection decision, increasing the level of aggressiveness of the weighting scheme increases the tracking error and exposure of the portfolio. In other words, the more aggressive the weighting scheme, the higher the exposure to the targeted factor will generally also be, and if the return to the factor is positive, the higher the return will generally be.

Figure 3.5 illustrates varying levels of aggressiveness in the weighting scheme. The lines represent sets of multipliers applied to securities or subportfolios. The steeper the slope of the multipliers, the more aggressive the weighting scheme is. This intuition can be extended to nonlinear weighting schemes as well.

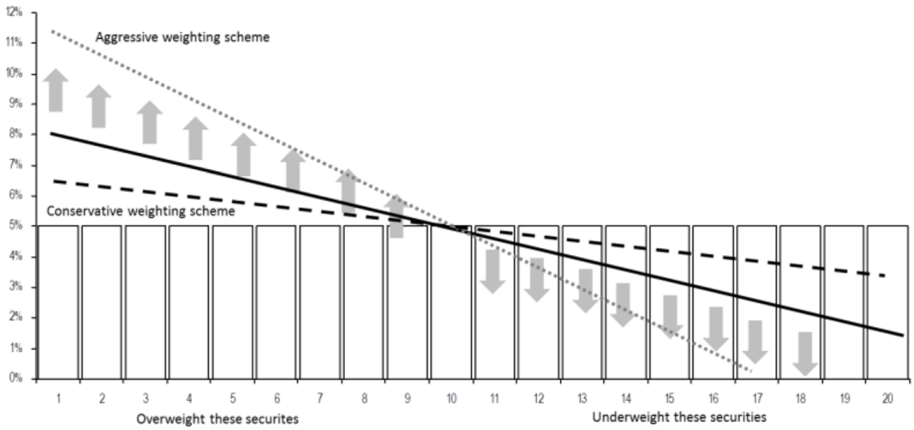
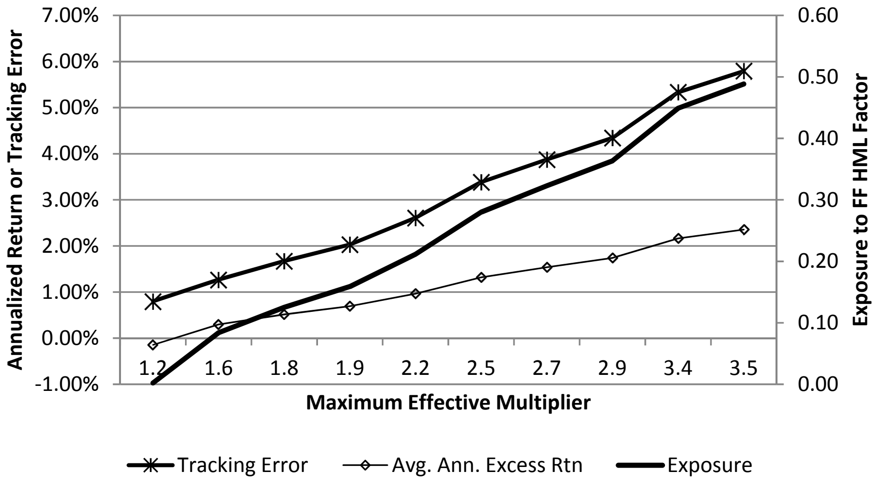


Figure 3.5. *The slope of the multipliers determines the aggressiveness of the weighting scheme*

An easy way to quantify the aggressiveness of a weighting scheme in a single metric is to use a measure called the MEM. The MEM is the largest effective multiplier in the portfolio, i.e. the weight of the security in the portfolio with the largest weight (relative to its market cap weight), divided by its market cap weight.

For linear weighting schemes, the MEM succinctly captures the effective slope of the multipliers. As the weighting scheme becomes more aggressive, i.e. the MEM increases, we expect tracking error and exposure to rise.

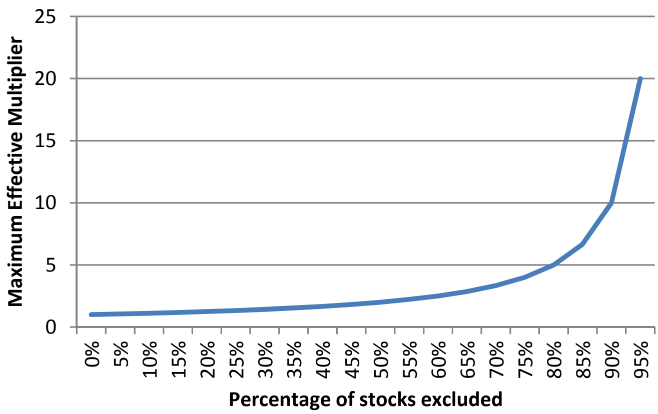
Returning to the previous value example, we employ a kinked linear multiplier scheme described in Appendix A to vary the MEM. As shown in Figure 3.6, increasing the MEM is associated with an increase in the tracking error, factor exposure and excess return. This is consistent with the security selection results for the same period.



Average Annualized Excess Return and Tracking Error are computed relative to MSCI World Index.

Figure 3.6. *The impact of changing the weighting scheme (Value Portfolio, April 1989–September 2014)*

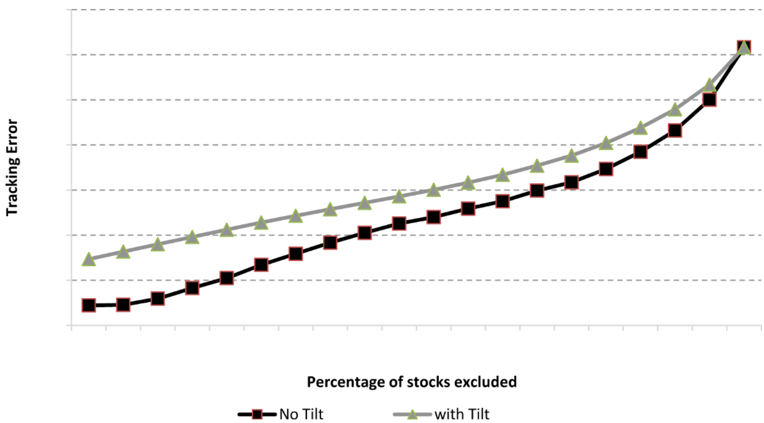
One last point we want to highlight is the interdependence of security selection and security weighting. To illustrate this, consider what happens to the MEM as we vary the amount of securities excluded. Here, we show the MEM as we remove successive percentages of the portfolio as we did earlier when evaluating security selection in isolation. The remaining securities are market cap weighted. The impact on MEM is nonlinear; as more and more securities are removed, the MEM rises exponentially after a certain point.



Starting universe and Benchmark is MSCI World Index.

Figure 3.7. *Maximum effective multiplier (for subportfolio) versus number of subportfolios removed*

This suggests that there will be nonlinear effects as we vary both the security selection and the weighting scheme together. Figure 3.8 illustrates two types of portfolios as we successively remove securities from the universe. In one portfolio, we market cap weight the remaining securities and in the other, we apply a fixed moderate tilt toward value in the remaining securities The impact on tracking error is shown in Figure 3.8. Here, the two lines gradually converge as more securities are excluded such that the more concentrated the portfolio is, the less of a relative impact the tilt, or weighting scheme, has on tracking error.



Starting universe and Benchmark is MSCI World Index.

Figure 3.8. *Impact on tracking error as more securities are excluded*

3.4. The maximum effective multiplier

In this section, let us take a closer look at the MEM.

3.4.1. *A closed-form solution to a limit on the MEM under certain assumptions*

In the previous section, we varied the MEM to show the impact on tracking error, exposure and return for a value portfolio. It turns out that we can derive a closed-form solution to the limit on the MEM under a set of specific assumptions. The assumptions are as follows:

1) the starting weights are equal weights;

2) the starting weights sum to 100%;

3) the multipliers are linearly interpolated between the minimum and maximum multipliers.

Recall that in the portfolio construction framework in the previous section, we ranked a universe of securities based on their factor characteristics and divided the securities into 20 subportfolios, each containing 5% of the market cap weight of the universe. Recall that we assigned multipliers to each subportfolio. Importantly, as long as the multipliers we assigned were linear, the MEM would never have exceeded 2. This result is powerful in that this is the only case we have found where there is a closed-form solution to a limit on the MEM. The proof behind this limit is given in Appendix B.

To recap, this observation can be generalized as follows:

As long as the starting weights are equal weights (i.e. each security or group of securities has the same weight), the set of weights sums to 100% and the multipliers are linearly interpolated, then the MEM will always be 2.

Interested readers will note that one consequence of this observation, in Figure 3.6, we had to in fact employ a kinked multiplier function because if we had instead used linear multipliers, the MEM could not have exceeded 2.

3.4.2. *Effective multipliers under generalized conditions*

What happens then if the three conditions required for the closed-form solution do not hold? What if we had used non-equal weights as a starting point or nonlinear multipliers, for instance? A closed-form solution for the MEM is no longer possible once we depart from these three assumptions. That said, we can make several observations about what the relationship between the actual multipliers we assign and the effective multipliers that result after rescaling the weights.

Let us start by assuming there are n securities and define the following vectors:

Starting weights: $S = \begin{bmatrix} s_1 \\ s_2 \\ \cdot \\ s_n \end{bmatrix}$ Multipliers: $Z = \begin{bmatrix} z_1 \\ z_2 \\ \cdot \\ z_n \end{bmatrix}$

Final weights: $W = \begin{bmatrix} w_1 \\ w_2 \\ \cdot \\ w_n \end{bmatrix}$ Effective multipliers: $E = \begin{bmatrix} e_1 \\ e_2 \\ \cdot \\ e_n \end{bmatrix}$

We derive a general relationship between the variables above (see Appendix C for details):

$$\boldsymbol{E = Z / ((Z \bullet S)' \times I)} \qquad [3.2]$$

Note in equation [3.2] that there is perfect linear relation between the multipliers and effective multipliers. The vector of effective multipliers ***E*** can be greater or less than the vector of actual multipliers ***Z*** based on whether $(Z \bullet S)' \times I$ is greater or less than 1

$$\text{If } \boldsymbol{(Z \bullet S)' \times I} > 1, \mathbf{E<Z} \qquad [3.2a]$$

$$\text{If } \boldsymbol{(Z \bullet S)' \times I} < 1, \mathbf{E>Z} \qquad [3.2b]$$

When are the effective multipliers ***E*** less than the initial assigned multipliers ***Z***? One clear case occurs when all multipliers in the vector ***Z*** are greater than 1. But for typical weighting schemes, we observe that ***Z*** is centered around 1, with some elements less than 1, and others greater than 1. If this is the case, then equation [3.2a] tends to hold when the starting weights are positively correlated to the multipliers. For instance, if the starting weights are market cap weights, this relationship would hold if larger cap securities generally receive higher multipliers as in a factor such as quality.

When are the effective multipliers greater than the actual multipliers? Again one clear case occurs when the multipliers in vector $\boldsymbol{Z}$ are all less than 1. (One example are the FTSE factor indices, which use scores that have been created using a cumulative normal mapping function that forces all scores to be between 0 and 1.) As before, if the multipliers are not all less than 1, equation [3.2b] tends to hold when the starting weights are negatively correlated to the multipliers such as in a factor like value.

3.5. Analyzing the MEM for several popular cases

In this section, we look at current popular weighting schemes and determine how much we can glean about the effective multipliers, and the MEM ideally, using the framework we have so far outlined. With this information, we can develop a better sense of the exposure and tracking error of the portfolio.

We will consider the following cases:

	Starting weights	Multiplier scheme
Case 1	Equal weights	Linear multiplier
Case 2	Cap weights	Linear multiplier
Case 3	Equal weights	Nonlinear multiplier: kinked set of multipliers
Case 4	Equal weights or cap weights	Nonlinear multiplier: cumulative normal distribution mapping function
Case 5	Equal weights or cap weights	Nonlinear multiplier: quasi-linear mapping function

Table 3.1. *List of popular smart beta weightings*

Cases 1 and 2: linear multiplier schemes

Case 1 was the case we examined in the previous section. There we showed that no matter what initial multipliers we assign, the effective multipliers are well characterized and the MEM is 2.

Case 2 describes what would happen if we were to use cap weights instead of equal weights as a starting point. Here, there is no closed-form solution to the limit on the MEM. This is because the distribution of market capitalization weights can take any shape.

If the starting weights are market capitalization weights and if the multipliers are linearly increasing from z_1 to z_n by increments of x, then we can derive the MEM as follows:

$$MEM = \frac{z_n}{(Z \bullet S)' \times I} >= \frac{z_1 + (n-1)x}{z_1 + (n-1)x} = 1 \qquad [3.3]$$

The proof is given in Appendix D. All we can say from equation [3.3] is that the MEM will be greater than or equal to one.

Case 3: equal weight as starting weight/nonlinear multiplier scheme (a kinked set of multipliers)

For this case, we assume that the starting weights are equal weights across the securities and that the multiplier scheme is kinked.

The multipliers z_1 to z_n take the form:

$$z_i = \begin{cases} 0, & \text{if } i \leq \lambda \\ (i - \lambda)x, & \text{if } i > \lambda' \end{cases} \qquad [3.4]$$

where:

– z_i = initial multiplier;

– i = rank of the security along the factor dimension in question (where a rank of 1 is the lowest rank);

– x = starting weight for the first security (e.g. the lowest ranked security);

– λ = breakpoint for the kinked function.

An illustration of a kinked multiplier scheme is shown in Figure 3.9.

As derived in Appendix D:

– if $\lambda = 1$, then the MEM = 2 (e.g. Case 1);

– if $1 < \lambda < n$, then the MEM = $\frac{2n}{1+n-\lambda}$ > 2, and it increases as λ increases.

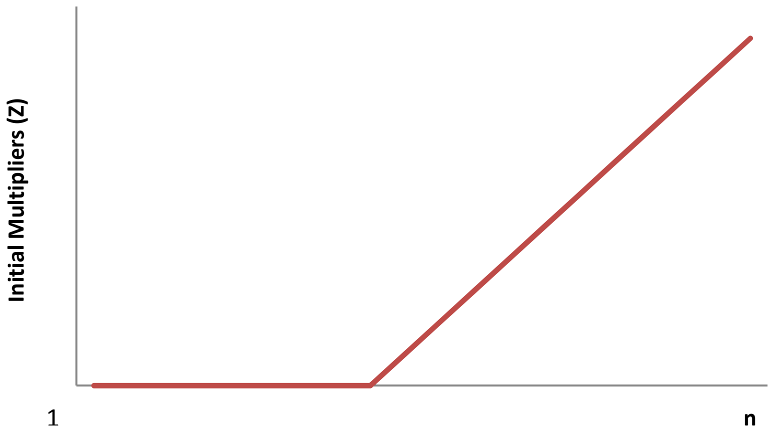


Figure 3.9. *Illustration of a kinked multiplier scheme*

For given values of n and λ, the MEM can be calculated using equation [3.18] shown in Appendix D. For instance:

– If $n = 100$, $\lambda = 10$, then the MEM = 2 × 100/(1 + 100 – 10) = 2.20

– If $n = 100$, $\lambda = 50$, then the MEM = 2 × 100/(1 + 100 – 50) = 3.92

Thus, the MEM for Case 3 can actually be calculated. The main takeaway is that the more stocks are excluded, the larger the MEM that can be achieved.

Case 4: Nonlinear multiplier scheme (a cumulative normal mapping function)

For this case, the starting point can be either equal weights or cap weights and the multiplier scheme is a nonlinear one utilizing a cumulative normal distribution mapping function. This mapping scheme is a technique that is used in the FTSE factor indices.

The multiplier scheme based on a cumulative normal distribution can be expressed as follows:

$$z_i = CN(\omega_i) = \int_{-\infty}^{\omega_i} \frac{e^{-x^2/2}}{\sqrt{2\pi}} dx \qquad [3.5]$$

Note that ω_i denotes a score, such as a z-score, typically calculated from raw security factor characteristics.

We can show that the effective multipliers are proportionally greater than their initial multipliers since:

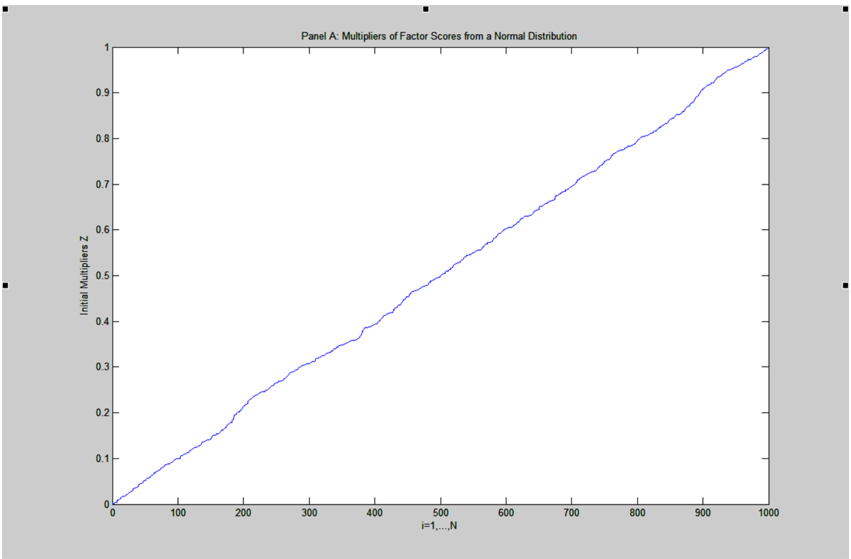
$$(Z \bullet S)' \times I = \sum_{i=1}^{N} CN(\omega_i) s_i < 1 \qquad [3.6]$$

since $CN(\omega_i) < 1$ by definition for all securities.

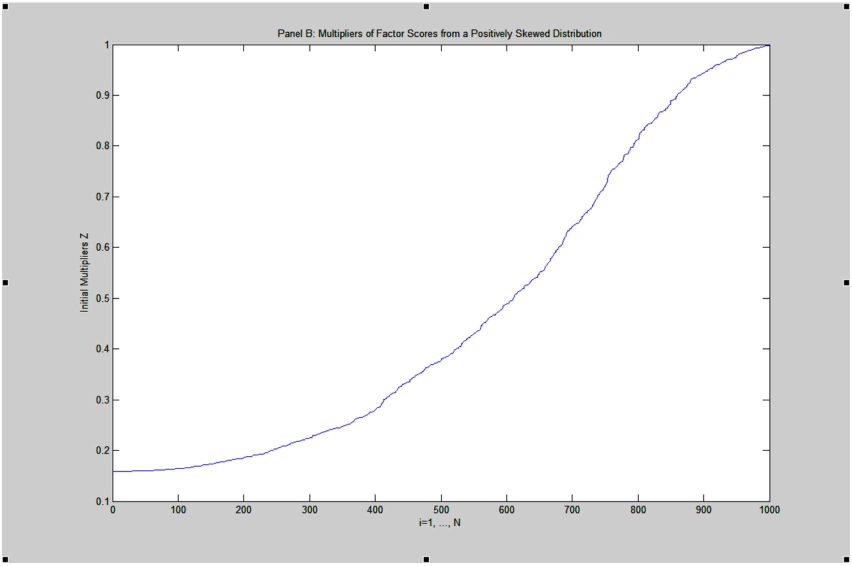
As one would expect, the distribution of the initial multipliers Z depends on the distribution of the underlying factor scores ω_i. If the scores are normally distributed, the multiplier scheme converges toward a linearly increasing function as N increases, and the derivation is as follows.

If ω_i is drawn from a normal distribution, and then sorted such that $\omega_1 < \omega_2 < \cdots < \omega_n$, and if we divide the security rank i by the total number of securities N, we obtain i/N in the range of 0–1, the same for the probability. In other words, $\omega_i = CN^{-1}(\frac{i}{N})$. Therefore, $z_i = CN(\omega_i) = CN(CN^{-1}\left(\frac{i}{N}\right) = \frac{i}{N}$. That is, multiplier z_i is approximately a linear function of security rank i, as illustrated in panel A of Figure 3.10.

a) *Normal distribution*:



b) *Positively skewed distribution*:



c) *Negatively skewed distribution*:

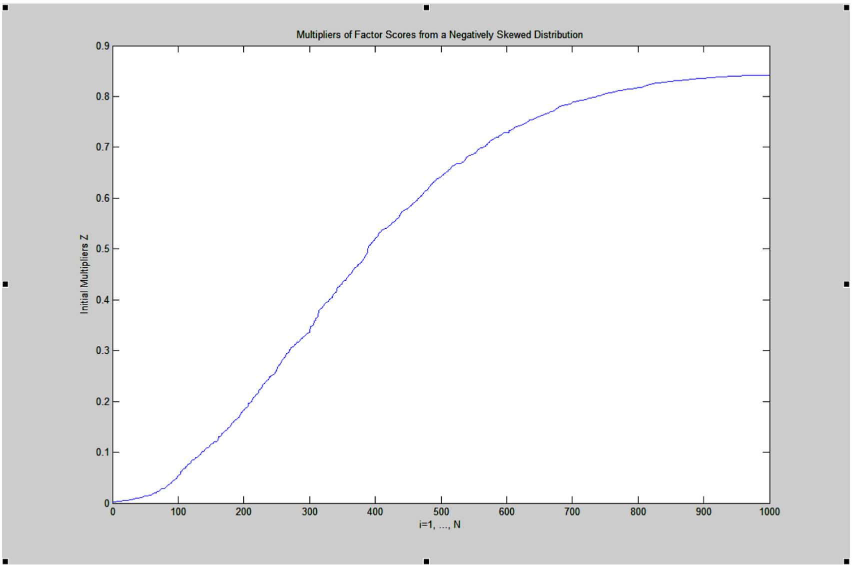


Figure 3.10. *Examples of initial multipliers for different underlying score distributions in a cumulative normal mapping function*

If the scores are skewed, the multipliers are nonlinear, and the way the nonlinearity plays out does not differentiate the tails significantly. This is illustrated in Figure 3.10.

As for the effective multipliers E, the elements in E are linearly related to the elements in Z, the initial multipliers, as we previously saw in equation [3.1]. Case 4 is in fact a special case of equation [3.2b] where effective multipliers are greater than the initial multipliers proportionally.

Case 5: Nonlinear multiplier scheme (a quasi-linear mapping function)

Applying a multiplier scheme that uses a quasi-linear mapping function is a technique that is used in the MSCI factor indices.

In this weighting scheme,

$$z_i = \begin{cases} 1/(1-\omega_i), & \text{if } \omega_i \leq 0 \\ 1+\omega_i, & \text{if } \omega_i > 0 \end{cases} \qquad [3.7]$$

Note that when ω_i is greater than 0, the function is linear and when ω_i is less than or equal to 0, the function is nonlinear.

Here, the effective multipliers are proportionally scaled initial multipliers, but can be either augmented or shrunk. This is shown as follows:

By construction,

$$0 < \frac{1}{1-\omega_i} < 1 \qquad [3.8]$$

and

$$1+\omega_i > 1 \qquad [3.9]$$

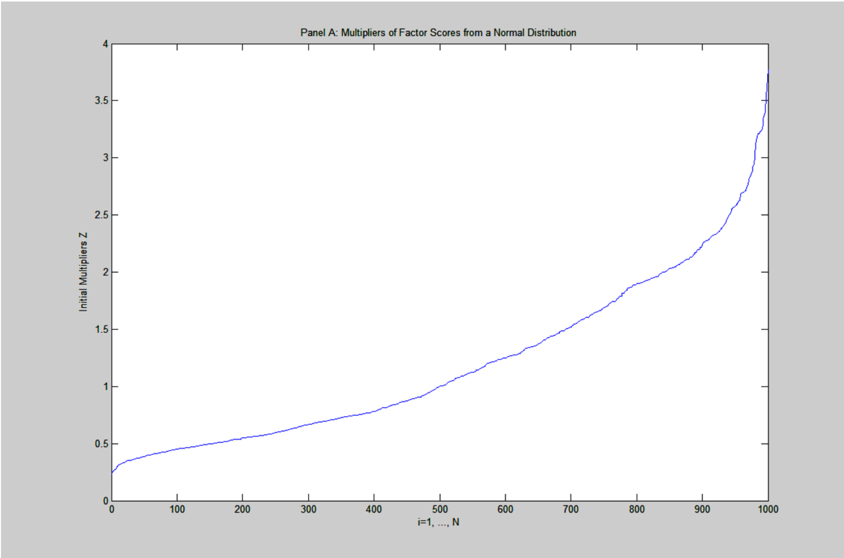
Thus,

$$(Z \bullet S)' \times I = \sum_{i=1}^{N} z_i s_i$$

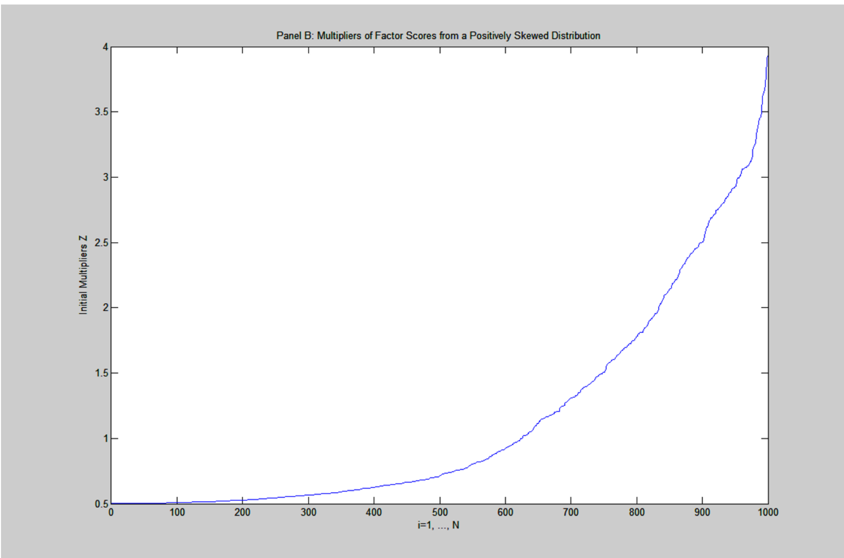
which can be greater than 1 or less than 1.

As in Case 4, the distribution of the initial multipliers depends on the distribution of the underlying factor z-scores. Regardless of normality of the factor z-scores or not, the resulting multipliers do not increase linearly. The nonlinearity of the multiplier schemes results in differentiating one of the two tails or both at an increasing speed depending on the distribution of the *z*-scores. This is illustrated in Figure 3.11.

a) *Normal distribution*:



b) *Positively skewed distribution*:



c) *Negatively skewed distribution*:

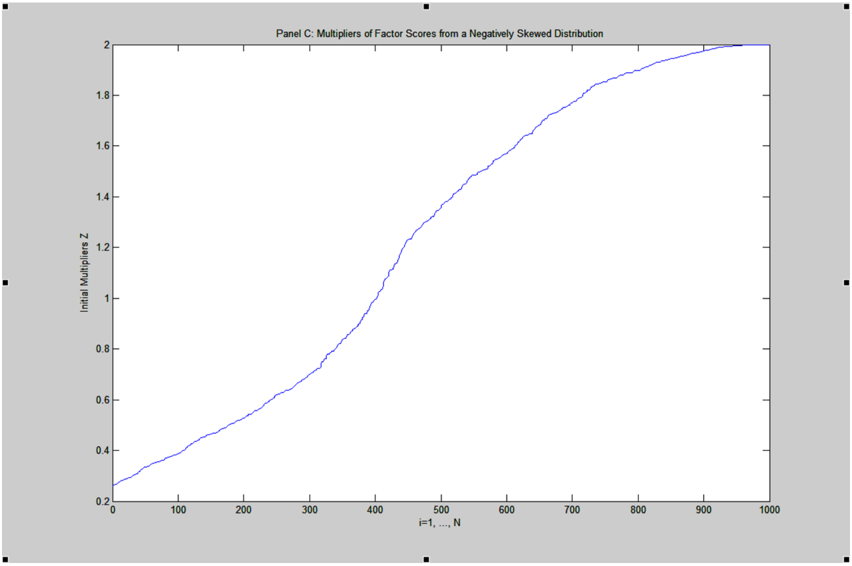


Figure 3.11. *Examples of initial multipliers for different underlying score distributions in a quasi-linear mapping function*

As for the effective multipliers *E*, the elements in *E* are linearly related to the elements in *Z*, the initial multipliers, as we previously saw in equation [3.1].

3.6. Conclusion

This chapter delves deeply into an area of rules-based portfolio construction that has largely been overlooked. We discuss the impact of screening and weighting decisions on portfolio characteristics and performance through the MEM, which is the largest effective multiplier in the portfolio, i.e. the weight of the security in the portfolio with the largest weight (relative to its market cap weight), divided by its market cap weight. The MEM is important in that it caps the concentration of the portfolio that drives performance, exposures and tracking error.

Regarding the MEM, there are a number of important findings in this paper. The first important finding is that we demonstrate that the MEM, if the starting weights are equal weights and the multiplier scheme is linear (i.e. a linear weighting scheme), is 2 if there is no stock screening. An MEM of 2 generally translates to tracking error of around 2–3% depending on the factor in question. Thus, to achieve higher levels of tracking error (via a higher MEM), either stock screening must be employed or the starting weights must be non-equally weighted or the multiplier scheme must be nonlinear. Stock screening is the easiest to control since there is a near monotonic relationship between the percentage of stocks screened and the tracking error. Using a non-equally weighted set of starting weights or a nonlinear set of multipliers requires robust calibration of how the modifications impact the entire distribution of security weights.

Second, the MEM is a function of the interaction between the starting weights and the multiplier scheme. If the starting weights are positively correlated with the multipliers (i.e. stocks with larger starting weights tend to get assigned higher multipliers such as in a quality factor portfolio), then the MEM will be higher.

Third, for nonlinear multiplier schemes derived from a cumulative normal distribution mapping function, the shape of the effective multiplier distribution depends primarily on the shape of the distribution of the factor z-scores.

In sum, rules-based portfolio construction appears relatively simple at first glance but, in fact, that perspective is misleading. Only recently has there started to appear more rigorous treatments of this area, primarily because mean variance optimization has traditionally been the academic workhorse for portfolio theory. Our hope is to turn the spotlight on an area we feel is largely and unduly overlooked and to illustrate some of the structural implications behind security selection and weighting decisions.

3.7. Appendices

3.7.1. *Appendix A: Description of the kinked multiplier scheme*

Here, we describe the kinked multiplier scheme we discussed in section 3.3. Recall in the body of the chapter we showed that any linear weighting scheme starting with equal weighted units has an MEM of 2, while a nonlinear convex or concave weighting scheme does not allow for easy calibration. The kinked multiplier scheme is a natural solution to this. Different schemes, along with their MEMs, are shown in Figure 3.12.

3.7.2. *Appendix B: Proof behind the limit to the MEM*

We can derive the MEM under the following conditions:

1) the starting weights are equal weights;

2) the starting weights sum to 100%;

3) the multipliers are linearly interpolated between the minimum and maximum multipliers.

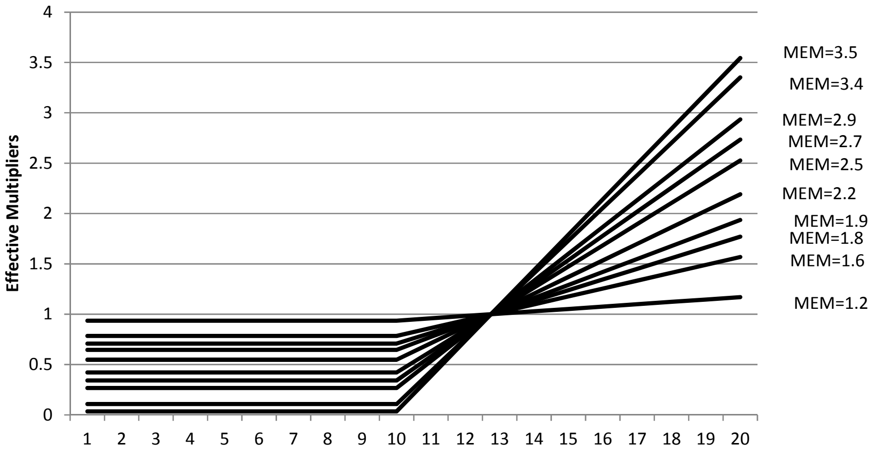


Figure 3.12. *Effective multipliers for a range of kinked multiplier schemes*

Recall from equation [3.1] that s_i is the starting weight and z_i is a multiplier applied to each security. Thus, a sample set of weights can be envisioned as shown in Table 3.2, where:

– n = the number of securities or group of securities;

– x = the weight of the first security or group of securities;

– y = the incremental weight for the remaining security or group of securities (where $n > 1$).

Security/subportfolio	1	2	3	–	N
Starting weight S_i	$1/n$	$1/n$	$1/n$	–	$1/n$
Multiplier z_i	x	$x + y$	$x + 2y$	–	$x + (n - 1)y$
Weight of the security/subportfolio	$x \times (1/n)$	$(x+y)\times(1/n)$	$(x+2y)\times(1/n)$	–	$(x+(n-1)y)\times(1/n)$

Table 3.2. *Weight as a function of the multiplier and starting weight*

We can solve for the MEM as follows:

$$\left(x+(x+y)+(x+2y)+.......+(x+(n-1)y)\right)\times\left(\frac{1}{n}\right)=1 \qquad [3.10]$$

We can solve for the MEM from the condition that the final tilted weights sum up to 1.

From equation [3.10], we can derive the upper bound of incremental weight, y, as a function of the number of securities or groups of securities, n,

$$y\le\frac{2}{(n-1)} \qquad [3.11]$$

And the weight of the first security or group of security, x, as a function of y and n

$$x=1-\frac{(n-1)}{2}y \qquad [3.12]$$

We can then show the MEM of security n or group n, $x+(n-1)y$, as follows:

$$\begin{aligned}&x+(n-1)y\\&=1-\frac{n-1}{2}\times y+(n-1)y\\&=1+\frac{n-1}{2}\times y\\&\le 1+\frac{n-1}{2}\times\frac{2}{n-1}\\&=2\end{aligned} \qquad [3.13]$$

Thus, the MEM can never exceed 2, or twice the starting weight.

By extension, in order to increase the MEM of a factor index, it must be the case that we:

1) use non-equal weights as a starting point;

2) use a nonlinear multiplier scheme;

3) use security selection such that we are not holding the entire universe.

3.7.3. *Appendix C: Deriving a general relationship between the initial multipliers and effective multipliers*

First, we solve for a generalization of the weighting scheme decision in the presence of any set of starting weights and any set of multipliers as follows.

Assume *n* securities, and define the following vectors:

Starting weights: $S = \begin{bmatrix} s_1 \\ s_2 \\ \cdot \\ s_n \end{bmatrix}$

Multipliers: $Z = \begin{bmatrix} z_1 \\ z_2 \\ \cdot \\ z_n \end{bmatrix}$

$$I = \begin{bmatrix} 1 \\ 1 \\ \cdot \\ 1 \end{bmatrix}$$

Using dot product multiplication to multiply the starting weights ***M*** by the multipliers ***Z***, the new "tilted" factor portfolio weights are $S \bullet Z = T$. ***T*** can be viewed as unnormalized tilted weights. The weights then must be scaled to sum to 100%. We denote this final set of weights for the tilted portfolio as ***W***.

$$W = \begin{bmatrix} w_1 \\ w_2 \\ \cdot \\ w_n \end{bmatrix}$$

Note that mathematically:

$$W = T/(T' \times I) \qquad [3.14]$$

Finally, we can compute the effective multiplier, which is the "actual" relationship between the starting weights *S* and the final weights *W*. So:

$$E = W \bullet / S \tag{3.15}$$

$$E = \begin{bmatrix} e_1 \\ e_2 \\ \cdot \\ e_n \end{bmatrix}$$

We can next derive the relationship between *E, Z* and *S*.

$$\begin{aligned} E &= W \bullet / S \\ &= T \bullet / S / (T' \times I) \\ &= Z \bullet S \bullet / S / (T' \times I) \\ &= Z / (T' \times I) \\ &= Z / ((Z \bullet S)' \times I) \end{aligned}$$

Thus,

$$E = Z / ((Z \bullet S)' \times I) \tag{3.16}$$

Equation [3.7] shows that there is perfect linear relation between ***E*** and ***Z*** because $(Z \bullet S)' \times I$ is simply a scalar. Specifically, as discussed in the chapter, we can see that the vector of effective multipliers *E* can be greater or less than the vector of actual multipliers ***Z*** based on whether $(Z \bullet S)' \times I$ is greater or less than 1.

3.7.4. *Appendix D: Derivations in section 3.5*

Derivation of Case 1B

If the starting weights are market capitalization weights and if the multipliers are linearly increasing from z_1 to z_n by increments of *x*, i.e. $z_2 = z_1 + x$, $z_3 = z_1 + 2x$, …, $z_n = z_1 + (n-1)x$, then we can derive the MEM as follows:

$$MEM = \frac{z_n}{(Z \bullet S)' \times I} \geq \frac{z_1 + (n-1)x}{z_1 + (n-1)x} = 1 \tag{3.17}$$

Since $(Z \bullet S)'\times I = \sum_{i=1}^{N} z_i s_i = z_1 + x(\sum_{i=2}^{n} s_i + \sum_{i=3}^{n} s_i + \cdots + \sum_{i=n}^{n} s_i)$.

Because $\sum_{i=1}^{n} s_i=1$ and $s_i \geq 0$, $\sum_{i=2}^{n} s_i \leq 1, \sum_{i=3}^{n} s_i \leq 1, \ldots, \sum_{i=n}^{n} s_i \leq 1$. Therefore, $(Z \bullet S)'\times I \leq z_1 + (n-1)x$.

Derivation of Case 2A

The derivation of the MEM for this case is as follows:

$$\frac{z_n}{(Z \bullet S)'\times I} = \frac{z_n}{\frac{x}{n}\times\frac{(1+n-\lambda)(n-\lambda)}{2}} = \frac{(n-\lambda)x}{\frac{x}{n}\times\frac{(1+n-\lambda)(n-\lambda)}{2}} = \frac{2n}{1+n-\lambda} \qquad [3.18]$$

since

$$(Z \bullet S)'\times I = \frac{x}{n}\times\frac{(1+n-\lambda)(n-\lambda)}{2} \qquad [3.19]$$

3.8. Bibliography

[BEN 13] BENDER J., BRIAND R., MELAS D. *et al.*, Foundations of factor investing, MSCI Research Insights, 2013.

[BEN 15a] BENDER J., BRIAND R., MELAS D. *et al.*, "Deploying multi-factor index allocations in institutional portfolios", in JURCZENKO E. (ed.), *Risk-Based and Factor Investing*, ISTE Press, London and Elsevier, Oxford, 2015.

[BEN 15b] BENDER J., WANG T., "Multi-factor portfolio construction for passively managed factor portfolios", in JURCZENKO E. (ed.), *Risk-Based and Factor Investing*, ISTE Press, London and Elsevier, Oxford, 2015.

[FAM 92] FAMA E.F., FRENCH K.R., "The cross-section of expected stock returns", *Journal of Finance*, vol. 47, pp. 427–465, 1992.

[FAM 93] FAMA E.F., FRENCH K.R., "Common risk factors in the returns on stock and bonds", *Journal of Financial Economics*, vol. 33, pp. 3–56, 1993.

[ROS 76a] ROSENBERG B., MARATHE V., Common factors in security returns: microeconomic determinants and macroeconomic correlates, Working paper, University of California Institute of Business and Economic Research, Research Program in Finance, No. 44, 1976.

[ROS 76b] ROSS S., "The arbitrage theory of capital asset pricing", *Journal of Economic Theory*, vol. 13, no. 3, pp. 341–360, 1976.

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4

Diversify and Purify Factor Premiums in Equity Markets*

In this chapter, we consider the question of how to improve the efficacy of strategies designed to capture factor premiums in equity markets and, in particular, from the value, quality, low-risk and momentum factors. We consider a number of portfolio construction approaches designed to capture factor premiums with the appropriate levels of risk controls aiming at increasing information ratios. We show that information ratios can be increased by targeting constant volatility (CV) over time, hedging market beta (HB) and hedging exposures to the size factor, i.e. neutralizing biases in the market capitalization of stocks used in factor strategies. With regard to the neutralization of sector exposures, we find this to be of particular importance for the value and low-risk factors. Finally, we look at the added value of shorting stocks in factor strategies. We find that with few exceptions the contributions to performance from the short leg are inferior to those from the long leg. Thus, long-only strategies can be efficient alternatives to capture these factor premiums. Finally, we find that factor premiums tend to have fatter tails than what could be expected from a Gaussian distribution of returns, but that skewness is not significantly negative in most cases.

4.1. Introduction

The emergence of a first generation of smart-beta strategies including minimum volatility, maximum diversification, risk parity and fundamental indexing approaches was a desperate response to the failure of traditional quantitative equity strategies and the poor equity market performance in 2008. But these smart-beta strategies were based on an illusion: that stock diversification is enough to generate

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returns or, in other cases, that weighting stocks using the fundamental data of a company matters in portfolio construction. It is now well known that neither is true.

It is, in fact, the exposure to factors such as low volatility or value that can fully explain the risk and return characteristics of first-generation smart-beta strategies, as demonstrated by Scherer [SCH 11] for minimum volatility, by De Carvalho *et al*. [DEC 12] for maximum diversification and risk parity approaches, and by Blitz and Swinkels [BLI 08] for fundamental indexing strategies. Investors now increasingly realize that what really matters is the factor exposure that you choose for portfolios. Choosing the right factor exposures should on average lead to good returns in excess of those of market capitalization indices. Thus, factor investing as we now understand it was born.

The philosophy of factor investing differs from past approaches, whether they are smart-beta or traditional equity quantitative investing strategies based on cross-sectional regressions as introduced by Haugen and Baker [HAU 96]. This is because factor investing is not about the stocks or diversification at stock level, but instead, it is entirely focused on the optimal exposure of a portfolio to the factors that generate a positive factor premium. It is the factor premiums that investors want to optimally capture and combine.

In this chapter, we show the importance of portfolio construction when it comes to capturing factor premiums efficiently. We first show that the simplest and most traditional approaches to factor investing tend to generate lower risk-adjusted returns because of uncontrolled risk and unwanted exposure to the market index or market capitalization biases. We show that strategies that target CV and hedge the market beta and exposure to size deliver higher information ratios. This is in particular due to a reduction in volatility. We also show the importance of removing sector exposure as an additional source of risk without return in factor investing. And we explain why long-only factor investing can rather efficiently capture factor premiums, in particular from the low-risk and momentum factors. Additionally, we demonstrate the importance of diversifying factors in each style because of the decorrelation of factor returns even within the same style. Finally, we show that factor premiums tend to exhibit fat tails, but also a relatively small skewness. Overall, we defend the importance of purifying and diversifying factor exposures in factor investing as one way of significantly improving risk-adjusted returns from factor strategies. And although this causes turnover to increase due to the need for additional trades, we highlight the fact that most of the benefits shown in this chapter can be captured in practice by using clever approaches to contain turnover.

4.2. Factors

Factors can be thought of as characteristics of stocks that are important to explain their risk and performance. According to the Capital Asset Pricing Model

(CAPM) of the 1960s, the performance of a stock should be determined by one single factor, i.e. the stock's exposure to the market portfolio. This is measured by a stock characteristic known as beta. The beta is calculated from estimating by how much a stock price moves in line with the price of the market portfolio, usually using a market capitalization index as a proxy.

However, as demonstrated in a large number of papers published since the 1970s, academics found that the CAPM cannot be verified empirically when tested with historical stock prices and more than one factor is needed to explain the performance and risk of stocks. Such papers highlighted that other factors play an important role. Today, it is widely accepted that factors such as the earnings yield, the market capitalization or stock price momentum also help explain stock returns, and more importantly, they can generate a positive premium. Such factors are said to be priced by the market.

4.2.1. *Raw factors*

Harvey *et al*. [HAR 16] list more than 200 factors that have been proposed in papers published in top academic journals to explain the cross-section of equity returns. However, many of these factors can be grouped into styles since they capture similar types of stock exposure. There are four main styles that we consider here: value, quality, low-risk and momentum. In each of these styles, we considered the factors that have been discussed more often in academic literature and that are likely to be recognized by readers familiar with factor investing in equities. In Table 4.1, we include the list of factors we used in each of these four styles.

For value, we considered a variety of ways to characterize a company's intrinsic value. Cheaper companies are typically identified by higher book-to-price and earnings-to-price ratios or higher dividend yields.

For quality we mixed factors related to assessing the competitiveness of businesses such as return-on-equity and other profitability related factors with factors related to agency problems such as accruals. Quality companies are typically characterized by higher profitability. Another dimension of quality is confidence in the competence and integrity of the management team. Lower accruals that signal a potential problem with earnings reporting is thus one quality factor.

With regard to low-risk, we considered low volatility, low beta, low residual volatility and, as recently proposed by Asness *et al*. [ASN 17], low correlation. Lower risk or low correlation companies are preferred. While other low-risk factors have been proposed, they tend to be highly correlated with these four or with combinations of these and different factors and thus have not been considered. These include downside volatility, value-at-risk, highly correlated with low volatility, or the LMAX of Bali *et al*. [BAL 16] fully explained by a combination of factors from different styles. Also note that factors such as BAB, BAC and SMAX from Asness *et al*. [ASN 17] already integrate elements of hedging market exposure or controlling for volatility and for that reason have not been include in this list of more basic factors. They could be considered as less sophisticated alternatives to the improvements in factor construction we introduce in this chapter.

Style	Factor	Factor description	Data source
	B/P WS	Book to price ratio	Worldscope
	DY WS	Dividend yield	Worldscope
	DY+Share.Repurchase WS	Dividend plus share repurchases to market cap value	Worldscope
	E/P WS	Earnings yield	Worldscope
	E/P LTM IBES	Earnings yield for last trailing twelve months	IBES
Value Factors	E/P NTM IBES	Consensus earnings yield for next twelve months	IBES
	EBIT/EV	EBIT to enterprise value ratio	Worldscope
	EBITDA/EV	EBITDA to enterprise value ratio	Worldscope
	Gross.Profit/EV WS	Gross profit to enterprise value ratio	Worldscope
	SALES/EV WS	Sales to enterprise value ratio	Worldscope
	FCF/MC WS	Free cash flow to market cap value ratio	Worldscope
	CFO/EV WS	Operating cash flow to enterprise value ratio	Worldscope
	Lev WS	Debt to asset ratio	Worldscope
	Asset.Tur WS	Asset turnover ratio	Worldscope
	Ext.Fin/A WS	External financing to asset ratio	Worldscope
	CAPEX-DEP&AMOR/A WS	Net capital expenditure to asset ratio	Worldscope
	ROE	Return on equity	Worldscope
	ROCE	Return on capital employed	Worldscope
	ROIC	Return on invested capital	Worldscope
Quality Factors	ROA	Return on assets	Worldscope
	EBIT/A WS	EBIT to asset ratio	Worldscope
	EBITDA/A WS	EBITDA to asset ratio	Worldscope
	Gross.Profit/A WS	Gross profit to asset ratio	Worldscope
	Gross.Income Mgn WS	Gross income margin	Worldscope
	FCF/A WS	Free cash flow to asset ratio	Worldscope
	CFO/A WS	Operating cash flow to asset ratio	Worldscope
	FCF-NI/A WS	Accrual accounting: free cash flow minus net income to asset ratio	Worldscope
	CFO-NI/A WS	Accrual accounting: operating cash flow minus net income to asset ratio	Worldscope
	Low Vol	Historical volatility	Factset
Low Risk Factors	Low Beta	Beta based on historical beta estimation	Factset
	Low Corr	Correlation based on historical estimation	Factset
	Low Res Vol	Residual volatility based on historical CAPM estimation	Factset
	12M-1M Ret	Twelve months minus one month total return momentum	Worldscope
	6M-1M Ret	Six months minus one month total return momentum	Worldscope
	1M Rev	One month mean reversion	Worldscope
	12M-1M IR	Information ratio over last twelve months excluding last month	Worldscope
Momentum Factors	12M-1M Alpha	Jensen alpha over last twelve months excluding last month	Worldscope
	12M-1M Alpha IR	Jensen alpha to its volatility over last twelve months excluding last month	Worldscope
	Up&Down 1M	One month changes in consensus earnings: up minus down to total number of estimations	IBES
	Up&Down 12M	Twelve month changes in consensus earnings: up minus down to total number of estimations	IBES
	SUE	Standard unexpected earnings	IBES
	SUFCF	Standard unexpected free cash flow	Worldscope

Table 4.1. *List of factors used for each style. We used 12 value factors, 16 quality factors, four low-risk factors and 10 momentum factors*

Finally, for momentum we include a number of measures of the performance of the stock of a company in the markets as well as the momentum of analyst earnings revisions. For momentum based on stock returns, we exclude the last monthly return since this is the standard approach in the literature. Stocks with the weakest recent performance are known to generate a positive premium and those with the strongest recent performance typically generate a negative premium, while companies with the strongest medium-term performances also generate a positive premium and companies with the weakest medium-term performances generate a negative premium. Medium-term momentum is thus a "follower", while short-term momentum is a contrarian indicator. We thus consider short-term momentum reversal as a separate factor.

4.2.2. *Factor premiums*

Factor premiums are the returns of a stock explained by its exposure to factors. The premiums of value stocks, low-volatility stocks, quality stocks, strongest trending stocks and smaller capitalization stocks have been positive on average over time for decades. Investors have an interest in tilting their portfolios in favor of such stocks to earn positive factor premiums. Conversely the premiums of expensive stocks, risky stocks, poor quality stocks, stocks with the weakest price trends and largest capitalization stocks have been negative on average over time. Investors do better to stay away from such stocks and avoid the negative premium, which would have reduced returns over time.

There are many papers dedicated to the question of why the factors behind these four styles generate a factor premium over time. Here, we skip this literature and go straight to the questions we want to address: to what extent can we improve the capturing of factor premiums by purifying them and to what extent can diversification of factors add value?

4.3. Results

4.3.1. *Factor z-scores*

Factors are typically not comparable. For example, the scale used to measure earnings yield is simply not comparable to the scale used to measure the book-to-price ratio. For this reason, a z-score transformation is usually applied in the cross-section of factors to center and reduce them to a common scale. The simplest version of the z-score transformation for factor j at a given point in time is:

$$z\text{-}score_f^i = \frac{f_i - \overline{f}}{\sigma_f}, \qquad [4.1]$$

where $z\text{-}score_f^i$ is the cross-sectional z-score of stock i for factor f, f_i is the value of the factor f for stock i at the chosen point in time, $\overline{f}$ is the average of all values of factor f for all stocks in the cross-section at that same time and σ_f is the cross-sectional volatility of the values of factor f for all stocks, also at the same time. In practice, we use a more sophisticated, but robust version of this definition that relies on the cross-sectional median rather than the average of factor f and removes outliers from the distribution of z-scores.

4.3.2. *Factor portfolio construction*

We compare different approaches to factor portfolio construction. The simplest strategy used to highlight the existence of factor premiums consists of ranking stocks by factor scores and then build a long-short portfolio every month, changing the allocation according to changes in those rankings. This long-short portfolio is invested in those stocks with the highest positive factor scores and sells short those stocks with the highest negative factor scores. A number of academic papers discuss this long-short portfolio by retaining a number of the highest ranked stocks in the long portfolio and selling short a similar number of the worst-ranked stocks. Equal weighting or market capitalization weighting of each of the retained stocks is common.

A slightly more sophisticated approach, which is also commonly used, is to make the weight w^i of each stock i in the long-short portfolio proportional to the respective $z\text{-}score_f^i$ of each stock as given by factor f:

$$w^i = 2\frac{z\text{-}score_f^i}{\sum_i \left| z\text{-}score_f^i \right|} \tag{4.2}$$

The leverage of the long-short portfolio is set at each monthly rebalancing at 2, i.e. 100% long and 100% short. We call this constant leverage (CL) factor strategy.

Sector neutrality is often imposed. One of the reasons for doing so is that for some factors the underlying information is not necessarily comparable from one sector to another. In the case of the sector-neutral (SN) strategy, we first divide the stocks in the universe into sectors. Here, we used the GICS definition based on 10 sectors that has been in use until the recent separation of the real estate subsect or from financials. We are not taking into account this split. In this case, each stock factor z-score is calculated for stocks in each respective sector. In this way, the factor strategy is SN by construction. We call this strategy CL SN. The weight of stock i in sector s in the long-short portfolio of factor f is given by:

$$w^{i,s} = 2\frac{z\text{-}score_f^{i,s}}{\sum_s \sum_i \left| z\text{-}score_f^{i,s} \right|} \tag{4.3}$$

A variant of the CL SN strategy can be constructed by simply allowing for the leverage to change every month at rebalancing, so as to target a given constant level of *ex ante* volatility $\sigma_{long-short}$ of the long-short portfolio based on scores as in [4.3]. We call this strategy the CV SN strategy and the stock weights are given by:

$$w^{i,s} = \frac{\sigma_{target}}{\sigma_{long-short}} z\text{-}score_f^{i.s} \qquad [4.4]$$

The *ex ante* volatility $\sigma_{long-short}$ is estimated from the historical variance covariance matrix of monthly stock returns over the previous 3 years and σ_{target} is the chosen target volatility. The use of CV strategies for factor investing was recently discussed by Perchet *et al*. [PER 14] for the value and momentum factors. The authors found that targeting CV significantly increased the information ratio of momentum factors. This was less so for value factors. The improvement in the information ratio was related to volatility clustering in the factor volatility and a negative correlation between factor premium and factor volatility, which was strong for momentum factors, but less strong for value factors.

We also considered a strategy similar to CV SN where, before calculating the *ex ante* factor volatility, we hedge the beta of the long-short portfolio against the market capitalization index (HB). This is an important exposure to hedge away to the extent that is possible and was proposed for low-risk factors by Frazzini *et al*. [FRA 13]. But hedging beta is also important for the other factors. For example, the beta of value factors for US stocks against the US market capitalization index was negative until about 2005 and has since become positive looking at the data available on Kenneth French's Website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). The contribution of a variable beta exposure adds to volatility and contributes to noise in the performance of simple factor approaches that do not attempt to hedge it away. This contribution from beta in non-neutral beta factor strategies can completely mask the factor premium as is the case for low-risk factors. To hedge the beta of the long-short portfolio, we calculate an *ex ante* beta for each stock from:

$$\beta^i = \frac{1}{3} + \frac{2}{3}\beta^i_{3year} \qquad [4.5]$$

where the β^i_{3year} is the historical beta for stock *i* at a given time *t* calculated from a regression of the stock returns in excess of cash returns against the market capitalization index returns in excess of cash returns using monthly total returns over the previous 3 years. This is a simplification of the use of Bayesian approaches in the estimation of stock beta and is proposed by data provider Bloomberg as adjusted beta. Frazzini *et al*. [FRA 13] use a similar approach, although employing different coefficients in the weighted average between a beta of 1 and the historical beta.

We use these stock betas to calculate the final *ex ante* beta β of the factor long-short portfolio at a given date. To hedge the beta of the factor portfolio, we simply subtract from the factor long-short portfolio the allocation of β times a portfolio long the market capitalization index and short cash at that point in time. The resulting portfolio is now beta-neutral (*ex ante*). We call this strategy CV SN HB.

We consider a variant of the CV SN HB strategy where not only the beta to the market is hedged, but also the exposure to size (HS) is neutralized. Indeed, factor strategies often show exposure to size by being biased to either smaller or larger capitalization stocks. Again, this will add to the volatility of the factor strategy and can mask the true factor premium. Fama and French [FAM 92] recognized the problem for value factors and proposed a simple approach to neutralize size exposures whereby factor portfolios are constructed after segmenting the universe into different market capitalization segments, and then applying the factor construction methodology in each segment. Because this process gets rather convoluted if we aim to simultaneously hedge the beta to the market and the size exposure while neutralizing sectors, we have opted for a different approach. We first estimate the beta of each stock to size at each rebalancing. We do this by regressing at that point in time the past stock returns in excess of cash returns against the past returns to a portfolio long the equally weighted (EW) index of all stocks in the universe and short the market capitalization index over the previous 3 years. The weighted average of stock-size betas gives the *ex ante* exposure β_{size} of the long-short factor portfolio to size. We can hedge the size exposure while keeping the portfolio market beta neutral simply by subtracting from the SN beta-hedged long-short factor portfolio the allocation to β_{size} times a portfolio long the EW allocation to all stocks in the universe and short the market capitalization portfolio times the market beta exposure of the EW portfolio. This is done before the estimation of the *ex ante* volatility and calibration of leverage to target a CV. We call this strategy CV SN HB HS.

Clarke *et al*. [CLA 17] revisited recently the use of cross-sectional factor regressions as a means of building portfolios with targeted factor exposures and removing unwanted factor exposures. In such approaches, the factor portfolio construction is different to that described above. For each factor there is a factor mimicking portfolio such that the product of the stock weights by its stock factor scores is 1 while the product of the stock weights by any other stock factor scores is 0. But this orthogonalization of factor exposures based on factor scores does not aim to orthogonalize factor returns, and targeting unit exposure in terms of factor scores is not comparable with targeting CV of factor returns. Moreover, this approach breaks down when factors with highly correlated scores are used, e.g. attempting to include the book-to-price and the earnings yield. And the stock weights in each factor mimicking portfolio change as soon as an additional factor is considered.

Our philosophy above is different and more practical than this more academic oriented cross-sectional regression methodology. In our view, what is important for investors is to remove unwanted factor exposures at the level of returns. It is the correlation of returns that needs to be handled. And the factor exposures should be targeted in terms of a risk budget allocation of factor returns, not factor scores.

4.3.3. *Impact of hedging beta and size, neutralizing sectors and targeting volatility*

In Table 4.2, we show the historical information ratios for the value, quality, low-risk and momentum factors at a global level (developed countries) and for the United States, Europe and Japan based on the different approaches to factor portfolio construction. We also include the aggregation of all factors from all styles in the last rows of the table. For the world, we used the stock universe defined by the MSCI World index from January 1997 to November 2016 and the results are in USD. For the United States, we used the universe defined by the S&P 500 index from January 1990 to November 2016 and the results are also in USD. For Europe, we used the stock universe defined by the STOXX Europe 600 index from January 1992 to December 1998 and the results are in historical German D-Mark and from January 1999 to November 2016 in EUR. Finally, for Japan we used the stock universe defined by the Topix 500 index from August 1993 to November 2016 and the results are in JPY. This means that while the results in Table 4.2 use the longest data available for each universe as provided by the data sources (MSCI, S&P Global, Stoxx and Topix), the starting date is not always the same with 20 years of data for the world universe and 27 years for the United States.

In the column “Average”, we show the average of the information ratio for all the factors of a given style calculated over the entire period. The factors used for each style were given in Table 4.1. The information ratio is simply the annualized average of returns from the monthly rebalanced factor strategy, using the portfolio factor construction indicated, divided by the annualized standard deviation of those same returns.

In the column “Aggregate”, we show the information ratio of all factors in a given style, EW, calculated over the entire period by considering the diversification effect from the fact that factor returns are not fully correlated, i.e. it is the information ratio we would observe had we invested in each of the individual factor strategies while allocating the same weight to each (no transaction costs included). The returns behind this information ratio are the same as in the column “Average”, but the volatility is lower due to the diversification effect. It is thus not surprising that in Table 4.2 the information ratio in the column “Aggregate” is always higher than the average information ratio for all factors in a style as given in the column “Average”.

A quick glance at Table 4.2 shows that for all styles except the value style, the information ratios tend to increase as we move down the table from CL to CV and then HB. This is in line with our expectations.

Informatio ratio		MSCI World		S&P 500		Stoxx Europe 600		Topix 500	
		Average	Aggregate	Average	Aggregate	Average	Aggregate	Average	Aggregate
Value Factors	CL	0.77	1.15	0.44	0.57	0.83	1.10	0.64	1.02
	CV	0.71	1.15	0.38	0.54	0.72	1.14	0.61	1.04
	CV HB	0.72	1.16	0.39	0.56	0.68	1.05	0.68	1.18
	CV HB HS	0.63	1.01	0.33	0.50	0.69	1.09	0.65	1.15
Quality Factors	CL	0.51	0.74	0.25	0.29	0.56	0.92	0.17	0.18
	CV	0.59	0.96	0.34	0.58	0.61	1.07	0.23	0.36
	CV HB	0.65	1.08	0.43	0.76	0.70	1.27	0.30	0.48
	CV HB HS	0.69	1.32	0.50	0.94	0.75	1.40	0.35	0.58
Low Risk Factors	CL	0.11	0.13	-0.13	-0.15	-0.01	0.00	0.00	-0.01
	CV	0.25	0.31	-0.04	-0.01	-0.05	-0.04	0.03	0.04
	CV HB	0.43	0.56	0.37	0.51	0.29	0.38	0.03	0.04
	CV HB HS	0.50	0.65	0.48	0.67	0.38	0.49	-0.08	-0.08
Momentum Factors	CL	0.35	0.43	0.23	0.21	0.61	0.78	0.24	0.24
	CV	0.42	0.59	0.32	0.46	0.75	1.09	0.28	0.39
	CV HB	0.49	0.70	0.36	0.52	0.79	1.18	0.32	0.42
	CV HB HS	0.54	0.82	0.39	0.60	0.90	1.34	0.34	0.48
All Factors	CL	0.43	0.65	0.21	0.28	0.50	0.80	0.26	0.39
	CV	0.49	1.06	0.26	0.69	0.51	1.39	0.29	0.66
	CV HB	0.57	1.30	0.39	1.05	0.62	1.75	0.33	0.76
	CV HB HS	0.59	1.47	0.43	1.22	0.68	1.88	0.32	0.72

CL = Constant Leverage HS = Size exposure is hedged Non Region Neutral
CV = Constant Volatility HB = Market Beta is hedged Sector Neutral

Table 4.2. *Historical information ratio for the value, quality, low-risk and momentum factors over the entire period. Different approaches were used in the construction of the long-short portfolio behind the factor strategies to measure the effects of changing leverage so as to target constant volatility (CL), hedge the exposure to the market (HB) and hedge size exposure (HS). Both the average of individual factor information ratios for each style and the information ratio based on the aggregation of the individual respective factors in each style is shown. The last set of rows considers all factors from all styles. The factor definitions can be found in Table 4.1. Total monthly returns were used. Results do not include transaction costs*

According to Perchet *et al*. [PER 14], the use of a CL approach should lead to an increase in the information ratio over that for the same factor strategy using a CL approach for as long as the factor volatility shows sufficiently strong clustering and even more if there is a negative correlation between factor returns and factor volatility. They showed that this was the case for momentum factors, but less so for value factors where they also did not observe any significant improvement in the information ratio. Here, we show that for both quality and low-volatility factors, the use of a CV approach increases the information ratio, thus suggesting that for these factors, volatility clustering must be strong, while it is also very likely that there is a negative correlation between the premium of these factors and their volatility.

The hedging of beta also seems to increase the information ratio across Table 4.2, in particular, for low-risk factors. It is not surprising that the low-risk factors benefit the most since they face a headwind from the defensive beta in the case that this is not hedged, i.e. the beta of the long-short allocation for low-volatility and low-risk factors is below zero, thus creating a negative contribution to returns over the long term from this negative exposure to the equity market risk premium. For the other factors, the hedging of beta, to the extent that is successful, should remove a contribution to returns that is not likely to add to performance, but that should increase volatility unless factor allocation could be associated with a positive market timing effect. We see no reason to expect so. Indeed, for the quality, low-risk and momentum factors we find that hedging beta improves the information ratios and this occurs despite the fact that we use a relatively simple model for estimating *ex ante* beta and we only hedge beta once a month at each rebalancing. The improvement of the information ratio is also significant in the aggregation of all factors from all styles, as seen from the last rows of Table 4.2. For value, in general, the impact of hedging beta on the information ratios was smaller than for the other factors and for European stocks it even decreases the information ratios slightly.

With regard to the hedging of the size exposures, we cannot always expect an improvement in the information ratio since factors with exposure to smaller capitalization stocks could have benefited from the small-cap premium. Indeed, for value factors, in particular at a global level, but also to some extent in the United States, we found a decrease in the information ratio signaling that small capitalization exposure may explain some of the performance of value factor at a global level if the exposure to size is not hedged. However, for the other factors we again find an improvement from hedging size exposures, which shows that any size exposure for other factors adds to factor volatility without sufficiently contributing to returns. This is in line, for example, with Asness *et al*. [ASN 15] who found size exposures to be negatively related to quality.

This set of different approaches to the implementing of factor strategies starting with exactly the same stock factor scores allows us to investigate the impact of different effects, namely risk budgeting as opposed to CL, the neutralization of the exposure to the market portfolio and the neutralization of any size exposure. We show that in general the purification of factor premiums arising from hedging beta and size exposure and from making sure that factor volatility remains constant over time leads to the highest information ratios.

The results shown in this section clearly highlight that purifying factors even in relatively simple ways can improve risk-adjusted returns either by removing unwanted risk exposures, and thus reducing risk, or by removing exposure that detracts value from factor returns, or a combination of both. We believe that factor investing approaches that pay attention to the purification of factor premiums can deliver higher risk-adjusted returns with a much lower correlation with equity market returns.

Finally, while this is so from a conceptual point of view, the success in capturing pure factor premiums is a function of the success in our ability to forecast beta and factor volatility. Perchet *et al*. [PER 14] documented the success of volatility forecasting in factor investing, at least for value and momentum equity factors. They found that factor volatility can be rather well controlled when factor portfolios are rebalanced daily. For monthly rebalancing, they suggest that even if factor volatility is less well controlled *ex post*, the improvement in the information ratio is still almost as high as when daily rebalancing is considered. Here, we extend the analysis to the quality and low-risk factors. Below we will look at the question of hedging beta in more detail.

4.3.4. *Beta of hedged factor strategy returns*

We will now focus on the efficiency of the process used to hedge the market exposure, i.e. the neutralization of beta. Here, we consider only the factor strategies managed with CV that are SN. In Table 4.3, we show the average over the entire period of the 3-year historical correlation of factor returns with the market capitalization index returns (in excess of cash returns) calculated every month. Again, we include the average of this metric across all factors in each style as well as the result obtained for the aggregation of all factors in each style. We compare the results for the factor strategy with and without hedging beta.

As expected, the most significant impact of the neutralization of beta on the correlations of the factor strategy returns with the market returns is felt by the low-risk factors with the absolute value of the correlation largely reduced. The overshooting of the beta-hedging strategy, reversing the sign of the correlation, is due to the simplicity of the model for *ex ante* beta used here. This overshooting means that the beta of the least risky stocks tends to be slightly higher than forecast and the beta of the riskier stocks tends to be slightly lower than forecast.

Average Correlation with market		MSCI World		S&P 500		Stoxx Europe 600		Topix 500	
		Average	Aggregate	Average	Aggregate	Average	Aggregate	Average	Aggregate
Value Factors	NHB	-6%	-5%	-8%	-10%	7%	14%	-18%	-29%
	HB	1%	5%	-4%	-5%	4%	8%	-10%	-16%
Quality Factors	NHB	-20%	-36%	-21%	-39%	-23%	-44%	-12%	-23%
	HB	-11%	-21%	-14%	-25%	-13%	-25%	-9%	-16%
Low Risk Factors	NHB	-63%	-71%	-50%	-59%	-60%	-69%	-67%	-73%
	HB	13%	18%	22%	34%	14%	21%	10%	11%
Momentum Factors	NHB	-20%	-30%	-16%	-23%	-19%	-27%	-10%	-16%
	HB	-13%	-19%	-12%	-17%	-15%	-22%	-4%	-7%
All Factors	NHB	-27%	-57%	-23%	-47%	-24%	-53%	-27%	-51%
	HB	-3%	-9%	0%	2%	-2%	-7%	-3%	-9%

HB = Market Beta is hedged
NHB = Market Beta is not hedged

Constant Volatility
Sector Neutral

Non Region Neutral
Size exposure is hedged

Table 4.3. *Historical average of the 3-year correlations of factor returns with the returns to the market capitalization index. Both the average of historical averages of 3-year correlations of the returns of each individual factor with the market capitalization index return and the historical average of the 3-year correlations of a style portfolio strategy based on the aggregation of the individual respective factors with the market capitalization index are shown. The factor definitions can be found in Table 4.1. Total monthly returns were used.*

In general, for the other factors we also observe a drop in the absolute value of this correlation, but it is smaller and starting from lower values. We note, however, that the absolute value of this correlation for the aggregation of all factors from all styles is rather small, attesting to the success of the beta-hedging strategy despite the fact that the model used here for *ex ante* beta is relatively simple. Our results confirm the success of beta-hedging strategies, in particular in multistyle multifactor portfolios, even when the hedging is implemented only once a month at the time of rebalancing.

4.3.5. *Sector neutralization*

We now investigate the importance of sector neutralization. We do so by considering a strategy where we simply remove the sector-neutralization step while still targeting a CV and hedging both market beta (HB) and size exposure (HS). We call this strategy CV HB HS. In Table 4.4, we compare the information ration of this strategy and that of the equivalent strategy with sector neutralization, named CV SN HB HS.

Removing sector neutrality has a negative impact on value factors and also, to some extent, on low-risk factors. The importance of neutralizing sector exposure in value factors is likely due to the fact that sectors can typically trade at value premiums or discounts relative to each other. Value is thus likely to matter within a sector, but not at sector level. That value tends to fail to generate a premium at the sector and industry level is known and was discussed by Doeswijk and van Pliet

[DOE 11], focusing in particular on dividend yields, and by Capaul [CAP 99], focusing on the price-to-book ratio.

Informatio ratio		MSCI World		S&P 500		Stoxx Europe 600		Topix 500	
		Average	Aggregate	Average	Aggregate	Average	Aggregate	Average	Aggregate
Value Factors	SN	0.63	1.01	0.33	0.50	0.69	1.09	0.65	1.15
	NSN	0.48	0.74	0.20	0.30	0.53	0.79	0.54	0.92
	t-stat	1.90	3.84	1.00	1.51	2.22	4.45	1.33	3.13
Quality Factors	SN	0.69	1.32	0.50	0.94	0.75	1.40	0.35	0.58
	NSN	0.67	1.32	0.51	0.94	0.75	1.37	0.37	0.61
	t-stat	-0.08	0.03	0.03	0.28	-0.06	0.37	0.05	-0.31
Low Risk Factors	SN	0.50	0.65	0.48	0.67	0.38	0.49	-0.08	-0.08
	NSN	0.51	0.61	0.33	0.42	0.46	0.56	-0.03	-0.03
	t-stat	-0.24	0.55	1.30	2.05	-1.19	-1.07	-0.53	-0.81
Momentum Factors	SN	0.54	0.82	0.39	0.60	0.90	1.34	0.34	0.48
	NSN	0.57	0.85	0.42	0.62	0.90	1.36	0.31	0.45
	t-stat	-0.53	-0.59	-0.14	0.03	-0.16	-0.42	0.22	0.58
All Factors	SN	0.59	1.47	0.43	1.22	0.68	1.88	0.32	0.72
	NSN	0.56	1.37	0.37	1.08	0.66	1.81	0.30	0.67
	t-stat	0.26	1.77	0.55	1.47	0.20	1.23	0.27	0.86

SN = Sector Neutral — Constant Volatility — Non Region Neutral
NSN = Non Sector Neutral — Market Beta is hedged — Size exposure is hedged

Table 4.4. *Historical information ratio for the value, quality, low-risk and momentum factors over the entire period. Two different approaches were used in the construction of the long-short portfolio behind the factor strategies that differ just by neutralizing sector exposure or not. The two strategies target constant volatility (CV), and hedge beta (HB) and size (HS) exposure. Both the average of individual factor information ratios for each style and the information ratio based on the aggregation of the individual respective factors in each style is shown. The last set of rows considers all factors from all styles. The factor definitions can be found in Table 4.1. Total monthly returns were used. Results do not include transaction costs*

The importance of neutralizing sector exposures in low-risk factors was discussed by De Carvalho *et al*. [DEC 15] who showed that the low-risk effect is strong in all sectors irrespectively of their volatility. Asness *et al.*'s [ASN 14] results based on neutralizing industry exposures corroborated the results of De Carvalho *et al*. Moreover, long-term biases toward interest rate sensitive sectors are known to form in low-risk equity factor strategies unless sector neutrality is imposed. Such biases tend to add to volatility and not to returns in the long term.

For the other factors we did not find any significant impact from removing sector neutrality, not even for momentum.

4.3.6. *Region neutralization in global strategies*

For the global factor strategies we also considered an additional factor approach in which we neutralize exposure to regions. This can be done by implementing a CV

SN HB HS factor strategy in different regions, thus achieving not only sector neutrality, but also region neutrality, while keeping beta and size neutrality. We considered three regions based on time zones: Asia and Oceania together, Europe and North America. The market beta of the final region-neutral and SN long-short factor portfolio as well as its size exposure are both hedged as before and the leverage is chosen so as to target a constant level of *ex ante* volatility at each rebalancing. We call this factor strategy CV SN HB HS RN.

In Table 4.5, we compare the information ratio of the CV SN HB HS strategy with the one introduced here that includes regional neutralization. The impact of neutralizing regional exposures is not clear. While for the value and low-risk factors region neutralization leads to a decrease in the information ratio, for momentum we see the opposite effect. For quality it is not clear since the average of the information ratio falls, but in aggregate, taking into account the diversification effect, the information ratio increases slightly.

Informatio ratio		MSCI World	
		Average	Aggregate
Value Factors	NRN	0.63	1.01
	RN	0.60	0.96
	t-stat	-0.39	-0.62
Quality Factors	NRN	0.69	1.32
	RN	0.65	1.36
	t-stat	-0.24	0.23
Low Risk Factors	NRN	0.50	0.65
	RN	0.46	0.57
	t-stat	-0.48	-0.85
Momentum Factors	NRN	0.54	0.82
	RN	0.62	0.95
	t-stat	0.86	1.42
All Factors	NRN	0.59	1.47
	RN	0.58	1.64
	t-stat	-0.06	1.44

RN = Region Neutral	Constant Volatility	Sector Neutral
NRN = Non Region Neutral	Market Beta is hedged	Size exposure is hedged

Table 4.5. *Historical information ratio for the value, quality, low-risk and momentum factors over the entire period. Two different approaches were used in the construction of the long-short portfolio behind the factor strategies which differ just by neutralizing regional exposures in global portfolios or not. The two strategies target constant volatility (CV), and hedge beta (HB) and size (HS) exposure. Both the average of individual factor information ratios for each style and the information ratio based on the aggregation of the individual respective factors in each style is shown. The last set of rows considers all factors from all styles. The factor definitions can be found in Table 4.1. Total monthly returns were used. Results do not include transaction costs*

From a practical point of view, neutralizing regions based on time zones is important because of trading. Trades in Asia and Oceania are implemented first, followed by Europe and then those in the North America. To preserve the neutrality of the beta to the market, it is easier to consider regional neutrality and to ensure that the market beta is hedged in each region. It is reassuring that for the aggregation of all factors from all styles, the impact on the information ratio seems negligible on average and that when taking into account the diversification effect across all factors from all styles the information ratio actually increases after neutralizing the exposure to the regions.

4.3.7. *Contribution from stocks with positive and negative factor scores*

In this section, we will look at the contribution to factor returns arising from both stocks with positive and negative factor scores. This is an important question for investors because even if factor premiums tend to be illustrated using paper trading long-short factor strategies, in practice, implementing such strategies is subject to transaction costs and constraints that are typically more significant for stocks with a negative exposure, i.e. those in the short leg of the factor strategy.

In Table 4.6, we compare the information ratio generated by the long leg of the factor strategies, by the stocks with positive factor scores, with the information ratio generated by the short leg of the strategy, by the stocks with negative factor scores. We first show the information ratio for the factor strategies managed with CV, sector neutral (SN) and with both the beta hedged (HB) and the exposure to size hedged (HS), as in Table 4.2. We call this strategy long-short in Table 4.6. Then, we show the information ratio for a factor strategy where the short leg is replaced by the market index. The size of the short leg needs to be adjusted so as to neutralize the beta. The exposure to size is hedged subsequently and the leverage is adjusted at the end to target a CV over time. We call this strategy long-market. The same exercise is repeated, but now replacing the long leg by the market index instead. We call this strategy market-short.

The results are striking and we believe they have not been reported yet in the literature, at least not to the extent we show here. Almost everywhere the information ratio of the long leg is higher than the information ratio of the short leg and in some cases quite significantly so. The two exceptions are for quality factors in Europe and momentum factors in the United States. And for momentum in Europe the difference is non-significant.

Information ratio		MSCI World		S&P 500		Stoxx Europe 600		Topix 500	
		Average	Aggregate	Average	Aggregate	Average	Aggregate	Average	Aggregate
Value Factors	Long-Short	0.63	1.01	0.33	0.50	0.69	1.09	0.65	1.15
	Long-Market	0.75	1.21	0.44	0.68	0.64	1.05	0.86	1.39
	Market-Short	0.23	0.34	0.16	0.24	0.55	0.82	0.25	0.39
Quality Factors	Long-Short	0.69	1.32	0.50	0.94	0.75	1.40	0.35	0.58
	Long-Market	0.72	1.09	0.51	0.84	0.60	0.89	0.49	0.72
	Market-Short	0.39	0.71	0.28	0.51	0.57	1.08	0.08	0.13
Low Risk Factors	Long-Short	0.50	0.65	0.48	0.67	0.38	0.49	-0.08	-0.08
	Long-Market	0.53	0.68	0.47	0.63	0.38	0.49	-0.10	-0.10
	Market-Short	0.38	0.49	0.45	0.64	0.34	0.45	-0.17	-0.19
Momentum Factors	Long-Short	0.54	0.82	0.39	0.60	0.90	1.34	0.34	0.48
	Long-Market	0.58	0.89	0.32	0.53	0.84	1.30	0.38	0.51
	Market-Short	0.40	0.59	0.41	0.61	0.85	1.26	0.12	0.15
All Factors	Long-Short	0.59	1.47	0.43	1.22	0.68	1.88	0.32	0.72
	Long-Market	0.65	1.51	0.44	1.38	0.62	1.63	0.41	0.85
	Market-Short	0.35	0.75	0.33	0.79	0.58	1.48	0.07	0.15

Constant Volatility — Size exposure is hedged, Market Beta is hedged — Non Region Neutral, Sector Neutral

Table 4.6. *Historical information ratio for the value, quality, low-risk and momentum factors over the entire period. A constant volatility long-short sector-neutral strategy with both the market beta and the size exposure hedged was used (long-short). A strategy consisting of the sector-neutral long leg of this portfolio against the market index at constant volatility with both the market beta and the size exposure hedged was also used (long-market) as well as an equivalent strategy with the market index against the short leg (market-short). Both the average of individual factor information ratios for each style and the information ratio based on the aggregation of the individual respective factors in each style is shown. The last set of rows considers all factors from all styles. The factor definitions can be found in Table 4.1. Total monthly returns were used. Results do not include transaction costs*

Average Correlation Long with Short	MSCI World		S&P 500		Stoxx Europe 600		Topix 500	
	Average	Aggregate	Average	Aggregate	Average	Aggregate	Average	Aggregate
Value Factors	47%	40%	43%	51%	43%	52%	37%	16%
Quality Factors	39%	9%	38%	16%	31%	5%	32%	20%
Low Risk Factors	86%	84%	80%	80%	84%	86%	69%	66%
Momentum Factors	73%	78%	77%	86%	75%	87%	59%	53%
All Factors	61%	37%	60%	53%	58%	51%	49%	21%

Constant Volatility — Size exposure is hedged, Market Beta is hedged — Non Region Neutral, Sector Neutral

Table 4.7. *Historical average of the 3-year correlation for value, quality, low-risk and momentum long-market factor strategy returns with the returns from the market-short factor strategy as defined in Table 4.6. Both the historical average of 3-year correlations of each individual long-market factor strategy returns with the market-short factor strategy return and the historical average of the 3-year correlation of a style portfolio strategy based on the aggregation of the individual long-market factor strategies with each matching market-short factor strategies are shown. The last set of rows considers all factors from all styles. The factor definitions can be found in Table 4.1. Total monthly returns were used. Results do not include transaction costs*

This observation has significant consequences. Based on these results, we can claim that when it comes to factor investing, in general, investors can earn their factor premiums more efficiently by disregarding the short leg for which structuring an investment is usually much more difficult and costly. Of course, the additional question is to what extent, even if the short leg seems to add less to returns, it introduces enough diversification to still justify implementing it. The answer can be obtained by comparing the information ratio of the long leg, long-market, with the information of the full factor strategy, long-short. Here, we find that indeed there are a few cases in which the short leg still improves risk-adjusted returns because of a diversification effect. However, when looking at the last entry in the table, "All Factors", when considering all factors from all styles combined, this is only the case for Europe, and before transaction costs and the impact of shorting constraints are considered.

In Table 4.7, we look further into this question by looking at the correlation of the returns from the long-market strategy with the returns to the market-short strategy. We can see that this correlation is high for both the momentum and low-risk factors. For value factors the level of correlation is lower, while for quality factors we find that the level of correlation can be quite low, in particular in the "Aggregate" column.

4.3.8. *Volatility, leverage and turnover of hedged factor strategies*

We now focus on the volatility control and on both the leverage and the turnover required for the implementation of the CV, SN strategies with the market beta hedged (HB) and size exposure hedged (HS). At each rebalancing, we target an *ex ante* volatility of 5% annualized. We chose 5% because at this level, and as we shall see below, the different factors will be running an average leverage of about 2 over time depending on the style considered. This is already significant for many practical applications.

Let us first start by looking at the realized volatility. In Table 4.8, in the "Average" columns, we show the average of the historical *ex post* volatility, calculated over the entire period, of the factor strategies in each style. We can see that on average the *ex post* volatility is close to 5% even if more often than not it is somewhat above this level. We note, however, that we only rebalance the factor long-short portfolios once a month, i.e. we do not rebalance intramonth even if the *ex ante* volatility moves away from the 5% target significantly. Taking this into account, we can consider that the control of volatility works reasonably well. The results are in line with those found for momentum and value factors by Perchet *et al.* [PER 14].

Ex-post volatility at 5% *ex ante* volatility	MSCI World		S&P 500		Stoxx Europe 600		Topix 500	
	Average	Aggregate	Average	Aggregate	Average	Aggregate	Average	Aggregate
Value Factors	5.8%	3.6%	5.8%	3.9%	5.9%	3.7%	6.1%	3.5%
Quality Factors	5.8%	3.0%	5.5%	2.9%	5.7%	3.1%	5.6%	3.4%
Low Risk Factors	5.4%	4.9%	4.9%	4.9%	5.4%	4.8%	5.4%	4.5%
Momentum Factors	5.4%	3.5%	5.6%	3.5%	5.2%	3.6%	4.7%	3.8%
All Factors	5.6%	2.4%	5.4%	2.1%	5.6%	2.2%	5.5%	2.7%

Constant Volatility | Size exposure is hedged | Non Region Neutral
Market Beta is hedged | Sector Neutral

Table 4.8. *Historical ex post volatility over the entire period for the value, quality, low-risk and momentum factors over the entire period. A constant-volatility long-short sector-neutral strategy targeting 5% volatility with both the market beta and the size exposure hedged was used. Both the average of individual factor historical ex post volatility for each style and the historical ex post volatility of a style strategy based on the aggregation of the individual factors is shown. The last set of rows considers all factors from all styles. The factor definitions can be found in Table 4.1 Total monthly returns were used. Results do not include transaction costs*

In the "Aggregate" columns of Table 4.8, we show the historical *ex post* volatility for the aggregation of all factors in each style. The values of *ex post* volatility come out below 5% and below the average of the factor volatilities in the same style because of the diversification effect arising from the decorrelation of factor premiums within that same style. Only for low-risk, where both factors in this style tend to be significantly correlated, is the *ex post* volatility only slightly below the average of their *ex post* volatilities. In the last set of rows, "All Factors", we can see an additional reduction in *ex post* volatility from the diversification due to further decorrelation in style returns.

In Table 4.9, we show the historical average leverage of the factor strategies over time. We show the average of historical average leverage for all factors in each style and also the average historical leverage of the aggregation of all factors in each style. The leverage includes all positions in the portfolio including those required for hedging purposes. A leverage of 2 means that for each US dollar allocated to the factor strategy, we invest one dollar in the long portfolio and sell stocks short to the value of one dollar to generate on average a volatility of 5% annualized. When we look at the leverage in the "Aggregate" column, we can see that the leverage is lower due to the diversification effect. But, as seen in Table 4.8, the volatility of the underlying aggregation of factors is also lower and if the aggregate factor strategies were releveraged to reach about 5% of volatility, then the leverage would rise back to around 2.

We can see that the leverage required for each factor is different. For quality, for which the average correlation between the long-market and the market-short legs of the long-short factor strategy is the lowest, the leverage is highest due to the diversification effect. For value the leverage is somewhat lower, in line with a somewhat higher correlation between the long and short legs of the portfolio. Finally, for momentum and low-risk, where the correlation of the long and short legs is highest, the leverage is smallest. For the aggregation of all factors from all styles, in the row “All Factors”, we can see that the leverage required for 5% volatility has been about 2 over time. This means that investors considering long-only diversified approaches fully invested in the stocks with the higher factor scores will find it difficult to generate tracking error risk against market indices much above 5%.

Average leverage at 5% *ex ante* volatility	MSCI World		S&P 500		Stoxx Europe 600		Topix 500	
	Average	Aggregate	Average	Aggregate	Average	Aggregate	Average	Aggregate
Value Factors	2.2	1.3	2.2	1.3	2.3	1.2	2.1	1.2
Quality Factors	2.6	1.3	2.4	1.2	2.4	1.2	2.0	1.0
Low Risk Factors	1.4	1.2	1.8	1.6	1.4	1.3	1.2	1.1
Momentum Factors	1.8	1.0	1.8	1.0	1.8	1.0	1.6	0.9
All Factors	2.0	0.8	2.1	0.7	2.0	0.7	1.7	0.6

Constant Volatility   Size exposure is hedged   Non Region Neutral
Market Beta is hedged   Sector Neutral

Table 4.9. *Historical average leverage for the value, quality, low-risk and momentum factors over the entire period. A constant-volatility long-short sector-neutral strategy targeting 5% volatility with both the market beta and the size exposure hedged was used. Both the average of individual factor historical average leverage for each style and the average historical leverage of a style strategy based on the aggregation of the individual factors is shown. The last set of rows considers all factors from all styles. The factor definitions can be found in Table 4.1. Total monthly returns were used. Results do not include transaction costs*

In Table 4.10, we show the one-way turnover of the factor strategies on average and in aggregate. The turnover includes the trading required to hedge beta and size and adjust the leverage at each rebalancing. Indeed, turnover is used not only to change stocks in both the factor long and short leg of the long-short portfolio as their exposure to factors changes over time, but also for adjusting leverage to target constant risk and for hedging the beta and size exposures.

The purification of factors, while generating higher information ratios, also requires high levels of turnover as shown. The question of effective turnover reduction without sacrificing risk-adjusted returns is thus crucial for investors. There are a number of ways to reduce turnover while still capturing to a great extent the improvement in the information ratios shown here. For example, from Table 4.6, we can see that shorting stocks can be replaced by shorting the market. This alone reduces turnover significantly and leads to higher information ratio as shown. Using market capitalization indices to short the market, which is feasible, leads to even better results than shorting the EW market portfolio as shown in Table 4.6. Finally, the use of optimizers as in Black–Litterman type approaches as described by

De Carvalho *et al.* [DEC 14] is also highly efficient in reducing turnover and associated costs while not sacrificing returns. However, a more detailed answer to the question of turnover reduction, while extremely important, falls outside the scope of this chapter.

Average turnover at 5% *ex ante* volatility	MSCI World		S&P 500		Stoxx Europe 600		Topix 500	
	Average	Aggregate	Average	Aggregate	Average	Aggregate	Average	Aggregate
Value Factors	361%	195%	337%	178%	363%	192%	370%	196%
Quality Factors	357%	178%	307%	148%	345%	166%	333%	179%
Low Risk Factors	186%	162%	236%	194%	199%	171%	163%	146%
Momentum Factors	694%	382%	658%	364%	659%	366%	641%	353%
All Factors	399%	151%	381%	140%	391%	145%	377%	150%

Constant Volatility   Size exposure is hedged   Non Region Neutral
Market Beta is hedged   Sector Neutral

Table 4.10. *Historical average of one-way turnover for the value, quality, low-risk and momentum factors over the entire period. A constant-volatility long-short sector-neutral strategy targeting 5% volatility with both the market beta and the size exposure hedged was used. Both the average of individual factor historical average turnover for each style and the average historical turnover of a style strategy based on the aggregation of the individual factors is shown. The last set of rows considers all factors from all styles. The factor definitions can be found in Table 4.1. Total monthly returns were used. Results do not include transaction costs*

4.3.9. *Skewness and kurtosis of hedged factor strategy returns*

There have been suggestions that factor premiums are risk premium compensation for negative skew in the distribution of returns from the factor long-short portfolio strategies designed to capture them. We thus look at the skewness and kurtosis of factor premiums after controlling for volatility and HB and size exposures. We focus here on the CV SN HB HS factor strategies.

A new methodology for estimating skewness was recently proposed by Lempérière *et al.* [LEM 17], who claim that indeed factor premiums tend to be explained by skewness. In fact, glancing at their Figure 7, we do not find evidence of a strong relationship between negative skewness and factor risk-adjusted returns since there are a number of outliers, and to us, even removing those, any relationship looks weak. Moreover, it is not possible to compare the skewness calculated using the traditional definition with the skewness calculated from their definition because it scales with an arbitrary constant and no methodology for its calibration is proposed. The magnitude of the skewness calculated from their definition is thus arbitrary and a function of the value chosen for this constant. Finally, as they correctly discuss, the traditional skewness definition is much more sensitive to extreme values than their own definition. For these reasons, we use the traditional skewness in our calculations.

In Table 4.11, we show the skewness of the distribution of returns from the value, quality, low-risk and momentum factors. As before, the column "Average" indicates the average of the skewness of each factor in each style and the column "Aggregate" is the skewness of the aggregation of all factors in the same style.

Skewness	MSCI World		S&P 500		Stoxx Europe 600		Topix 500	
	Average	Aggregate	Average	Aggregate	Average	Aggregate	Average	Aggregate
Value Factors	-0.1	-0.4	0.0	-0.1	0.0	-0.2	-0.2	-0.3
Quality Factors	-0.1	0.0	0.0	0.1	0.0	0.0	-0.1	0.0
Low Risk Factors	-0.3	-0.4	-0.8	-0.9	-0.3	-0.5	-0.6	-0.6
Momentum Factors	-0.2	-0.6	-0.5	-0.8	-0.1	-0.2	-0.1	0.0
All Factors	-0.2	0.2	-0.4	-0.6	-0.1	0.0	-0.2	-0.6

Constant Volatility   Size exposure is hedged   Non Region Neutral
Market Beta is hedged   Sector Neutral

Table 4.11. *Skewness of the distribution of returns from the value, quality, low-risk and momentum factors over the entire period. A constant-volatility long-short sector-neutral strategy with both the market beta and the size exposure hedged was used. Both the average of individual factor skewness of returns for each style and the skewness of returns from a style strategy based on the aggregation of the individual factors is shown. The last set of rows considers all factors from all styles. The factor definitions can be found in Table 4.1. Total monthly returns were used. Results do not include transaction costs*

A general rule of thumb for skewness is that a value below –1.0 or above +1.0 is significant. A value between –1.0 and –0.5 and between +0.5 and 1.0 is moderately significant and values between –0.5 and +0.5 are not significant. The skewness of the distribution of returns of the MSCI World index over the same period was –0.7.

Although most of the skewness values in Table 4.6 are negative, they tend to fall between –0.5 and +0.5 and thus are non-significant. Moreover, the highest reading is for low-risk factors in Japan, where the skewness reaches –0.7. But in fact, from Table 4.1, low-risk factors in Japan had the lowest premium in the table, paying no premium at all on average in the period considered in this study.

Based on these results for factor strategies that purify factor premiums by removing exposure to the market and to size as much as possible, neutralizing sector exposures and controlling for risk over time, it appears that while negative skew may play a small role in explaining the premiums of some factors, it cannot be considered as the main explanation, not even for low-risk. Our results seem to be in line with the conclusion of Post *et al.* [POS 08] that the impact of skewness on factor premiums should be marginal.

In Table 4.12, we show the excess kurtosis of the distribution of returns of the same factor strategies for which the skewness of returns was shown in Table 4.11. For most factors, we find that the distribution of returns is leptokurtic and thus with fatter tails than the normal distribution. Momentum factors seem to exhibit slightly higher excess kurtosis than the other factors with the exception of Europe. The excess kurtosis for the distribution of returns of the MSCI World index in the same period is 1.5. The excess kurtosis of factors as given in Table 4.12 is often above this value, suggesting that some factors have even fatter tails than those found in the distribution of returns from the market capitalization index.

To conclude, in this section we find that although the distribution of factor returns tends to show either no skewness or in some cases just a small negative skewness, they do appear to exhibit fatter tails than what would be expected from a normal distribution, and sometimes even fatter tails than for the market index.

Excess kurtosis	MSCI World		S&P 500		Stoxx Europe 600		Topix 500	
	Average	Aggregate	Average	Aggregate	Average	Aggregate	Average	Aggregate
Value Factors	1.3	2.2	1.1	1.1	1.3	0.8	1.8	1.2
Quality Factors	1.9	1.2	0.9	0.5	0.9	0.2	2.1	3.0
Low Risk Factors	1.3	1.6	1.6	1.5	1.8	1.6	1.5	1.6
Momentum Factors	2.3	3.2	2.4	2.3	1.4	1.0	1.6	2.7
All Factors	1.7	2.4	1.5	0.6	1.3	0.2	1.8	4.1

Constant Volatility Size exposure is hedged Non Region Neutral
Market Beta is hedged Sector Neutral

Table 4.12. *Excess kurtosis of the distribution of returns from the value, quality, low-risk and momentum factors over the entire period. A constant-volatility long-short sector-neutral strategy with both the market beta and the size exposure hedged was used. Both the average of individual factor excess kurtosis of returns for each style and the excess kurtosis of returns from a style strategy based on the aggregation of the individual factors is shown. The last set of rows considers all factors from all styles. The factor definitions can be found in Table 4.1. Total monthly returns were used. Results do not include transaction costs*

4.4. Conclusions

In this chapter, we propose a number of improvements to common factor investing approaches which in our view play an important role in increasing the efficacy of factor investing. We focus in particular on the importance of risk management in factor investing. First, we generalize the results of Perchet *et al.* [PER 14] showing that targeting risk is important for factor investing. Indeed, we show that not only for the momentum factor, but also for the low-risk and quality factors, the use of target-risk strategies improves the information ratios when we compare these to what we obtain from similar strategies that do not control for risk. Second, we show that hedging beta and size exposures also leads to higher information ratios. Strategies that do not hedge beta or size exposures typically have higher volatility caused by non-controlled exposure to the market or market capitalization biases that leads to lower information ratios. We show that purified factor strategies have higher information ratios and that controlling for risk and removing unwanted exposures is beneficial across the board. We also find that in general neutralizing sector exposures tends to lead to higher information ratios.

Ex post, we find that the *ex ante* neutralization of market beta does indeed reduce the correlation of the returns from the factor strategies with those of the market capitalization index despite the fact that we considered a relatively simple model for *ex ante* beta and hedged the beta only once per month when rebalancing the portfolio. The neutralization of beta is particularly important for low-risk factors.

We find that the return contribution of factor premiums arising from investing in stocks with the highest factor scores is higher than the return contribution from selling the stocks with the worst factor scores short. This is a quite general result with important implications since the correlation between these two contributions toward the factor premium tends to be high for the low-risk and momentum factors in particular. This has significant practical consequences and means that factor investing can relatively efficiently rely only on the stocks with the highest scores, avoiding the operational complexity and costs associated with selling the stocks with the worst factor scores short.

Our results show that when using factor strategies that control for risk and hedge unwanted exposures, the distribution of factor returns tends to exhibit a relatively small skew. On the other hand, factor premiums tend to show fatter tails than expected from Gaussian distributed returns, even when controlling for *ex ante* volatility.

Our results indicate that the use of more than one factor in each style does lead to an improvement in the information ratios arising from the diversification effect. This is caused by the fact that factors in one same style show a certain level of decorrelation.

Despite the high levels of turnover resulting from the risk management and hedging of unwanted exposures in factor investing, these results are of great importance for investors. While not discussed here, there are efficient ways in particular based on the use of portfolio optimization that can efficiently reduce turnover without sacrificing the merits of the approach.

4.5. Bibliography

[ASN 14] ASNESS C.S., FRAZZINI A., PEDERSEN L.H., "Low-risk investing without industry bets", *Financial Analysts Journal*, vol. 70, no. 4, pp. 24–41, 2014.

[ASN 15] ASNESS C., FRANZZINI A., ISRAEL R. *et al.*, Size matters if you control your Junk, Working Paper, SSRN 2553889, US and Denmark, available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2553889, 2015.

[ASN 17] ASNESS C., FRAZZINI A., GORMSEN N. *et al.*, Betting against correlation: testing theories of the low-risk effect, Working Paper, SSRN 2553889, US and Denmark, available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2913508, 2017.

[BLI 08] BLITZ D.C., SWINKELS L.A.P., "Fundamental indexation: an active value strategy in disguise", *Journal of Asset Management*, vol. 9, no. 4, pp. 264–269, 2008.

[CLA 17] CLARKE R., DE SILVA H., THORLEY S., "Pure factor portfolios and multivariate regression analysis", *The Journal of Portfolio Management*, vol. 43, no. 3, pp. 16–31, 2017.

[DEC 12] DE CARVALHO R.L., LU X., MOULIN P., "Demystifying equity risk-based strategies: a simple alpha plus beta description", *The Journal of Portfolio Management*, vol. 38, no. 3, pp. 56–70, 2012.

[DEC 14] DE CARVALHO R.L., LU X., MOULIN P., "An integrated risk-budgeting approach for multi-strategy equity portfolios", *Journal of Asset Management*, vol. 15, no. 1, pp. 24–47, 2014.

[DEC 15] DE CARVALHO R.L., ZAKARIA M., LU X. *et al.*, "Low risk anomaly everywhere: evidence from equity sectors", in JURCZENKO E. (ed.), *Risk Based and Factor Investing*, ISTE Press, London and Elsevier, Oxford, 2015.

[DOE 11] DOESWIJK R., VAN PLIET P., "Global tactical sector allocation: a quantitative approach", *The Journal of Portfolio Strategies*, vol. 38, no. 1, pp. 29–47, 2011.

[CAP 99] CAPAUL C., "Asset-pricing anomalies in global industry indexes", *Financial Analysts Journal*, vol. 55, no. 4, pp. 17–37, 1999.

[FAM 92] FAMA E., FRENCH K., "The cross-section of expected stock returns", *Journal of Finance*, vol. 47, no. 2, pp. 427–465, 1992.

[FRA 13] FRAZZINI A., PEDERSEN L.H., "Betting against beta", *Journal of Financial Economics*, vol. 111, pp. 1–25, 2013.

[HAR 15] HARVEY C.R., LIU Y., ZHU H., "... And the cross-section of expected returns", *Review of Financial Studies*, vol. 29, no. 1, pp. 1–64, 2015.

[LEM 17] LEMPÉRIÈRE Y., DEREMBLE C., NGUYEN T.T. *et al.*, "Risk premia: asymmetric tail risks and excess returns", *Journal of Quantitative Finance*, vol. 17, no. 1, pp. 1–14, 2017.

[PER 14] PERCHET R., DE CARVALHO R.L., HECKEL T. *et al.*, "Inter-temporal risk parity: a constant volatility framework for equities and other asset classes", *Journal of Investment Strategies*, vol. 4, no. 1, pp. 19–41, 2014.

[POS 08] POST T., VAN VLIET P., LEVY H., "Risk aversion and skewness preference", *Journal of Banking and Finance*, vol. 32, pp. 1178–1187, 2008.

[SCH 11] SCHERER B., "A note on the returns from minimum variance investing", *Journal of Banking and Finance*, vol. 18, pp. 652–660, 2011.

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5

The Predictability of Risk-Factor Returns

This chapter explores the predictability of risk-factor investment returns using a range of combination forecast models. We find evidence that single-variable forecasts can be combined to produce risk-factor return estimates that are economically and statistically significant. Forecast effectiveness, however, varies depending on the risk factor modeled and the weighting method employed to combine individual forecasts.

5.1. Introduction

The debate on the effectiveness of return predictability continues in academia while industry practitioners maintain an insatiable appetite for new insights into the predictability of investment returns. Only recently has the focus turned to the predictability of risk factors. To date, this literature has been limited to only a few studies that focus on *single-variable* forecasting models. This chapter contributes to the literature by examining the predictability of risk-factor investment returns using *combination* forecasting techniques. The overarching objectives of this chapter are to examine whether individual forecasts of risk-factor returns can be combined to create statistically and economically significant forecasts.

In the spirit of Rapach *et al*. [RAP 10] and Kong *et al.* [KON 11], this chapter applies the combination model approach to forecast risk-factor investment returns. Specifically, five different combination models are employed to forecast six widely researched risk factors: size, market, value, momentum, credit and term. The statistical significance of these forecasts is examined using the out-of-sample R^2 statistic of Campbell and Thompson's [CAM 08] and the Clark and West's [CLA 07] test of significance. The return forecasts are also employed in the

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mean-variance framework to evaluate the economic significance of the forecasts in a portfolio selection context. Following on from Rapach *et al.* [RAP 10] and using the mean-variance analysis framework of Markowitz [MAR 52], this chapter compares the utility obtained from combination and sample-based forecasts of returns when they are employed in the mean-variance analysis framework[1]. Any differences in portfolio utility can be considered as the equivalent fees an investor would be willing to pay to use the combination forecasts.

This chapter reveals evidence that the combination forecast models produce statistically significant results for four of the six risk factors. While forecasts based on *single* economic variables are rarely statistically significant, models that *combine* these forecasts are found to be more effective. The results confirm the effectiveness of the combination models in forecasting the market risk factor, as well as demonstrating that forecasts of the value and credit risk factors are statistically significant. It is revealed that forecasts of the size risk factor vary in statistical significance depending on the weighting scheme employed, while all five of the combination model forecasts for each of the momentum and term risk factors lack statistical significance.

When combination forecasts are employed in the mean-variance framework, the majority of these forecasts provide economically significant improvements over historical average sample-based return forecasts. When forming portfolios of a single risk factor and the risk-free asset, it is found that the majority of combination forecasts result in average utility gains relative to the historical average forecasts. The combination forecasts offer average utility gains of between 0.69 and 1.91% relative to those achieved using the historical average forecasts for five of the six risk factors. When applied to the term risk factor, the combination forecasts achieve lower levels of utility.

The debate surrounding the predictability of returns and the efficacy of employing return forecasts in the portfolio selection decision continues. This chapter reports evidence that risk-factor return forecasts can be both statistically and economically significant; however, performance varies across combination weighting techniques and risk factors. This chapter is structured as follows. Section 5.2 reviews the related literature relevant to the topic. Section 5.3 outlines the forecast methodologies employed in this chapter and section 5.4 describes the data employed in the forecasts. Section 5.5 details the empirical results examining the performance of the single economic variable and combination forecasts. Section 5.6 offers concluding remarks.

1 Following from Rapach *et al.* [RAP 10], quadratic utility is considered.

5.2. Literature review

Return predictability has been extensively researched in the extant finance literature. While there is extensive evidence in support of equity market predictability, it is generally weak in an out-of-sample context[2]. Welch and Goyal [WEl 08], for example, examine an extensive list of equity market predictors and show that, in general, they generate poor results both in- and out-of-sample. Confusing the topic further, Cenesizoglu and Timmermann [CEN 12] note that while the association between statistical and economic significance is generally positive, the relationship is weak. While the statistical performance of predictions may be poor, this does not imply they are of no economic value.

Similarly, evidence of predictability in risk factors is mixed. Kao and Shumaker [KAO 99], Asness *et al.* [ASN 00], Ahmed *et al*. [AHM 02], Levis and Tessaromatis [LEV 04], L'Her *et al*. [LHE 07] and others find evidence of predictability when forecasting single risk factors. Studies on the predictability of multiple risk factors are rare, however. Asness *et al.* [ASN 17] find lacklustre evidence in support of timing across risk factors, using valuation and momentum signals. Arnott *et al.* [ARN 16, ARN 17], however, argue in favor of predictability using valuation metrics to forecast future returns. Although the evidence of risk-factor predictability is somewhat underwhelming, these studies have typically focused on single variable forecasts of risk-factor returns.

Despite the poor results of individual forecasts in the risk factor and wider asset class literature, it is possible that they may be employed in a statistically and economically meaningful way. Rapach *et al.* [RAP 10] show that by *combining* economic models, it is possible to produce forecasts that are statistically and economically significant[3]. Using the forecasting variables in Welch and Goyal [WEL 08], Rapach *et al.* [RAP 10] show that the results of individual regression models can be combined to provide useful forecasts of equity market returns. The combination forecasts decrease the uncertainty and instability risk associated with single model forecasts resulting in improved forecasting performance.

Although widely used in the economic literature, the combination model approach has only recently been applied in financial research[4]. Following Rapach *et al.* [RAP 10], the work of Kong *et al.* [KON 11] demonstrates that combination

2 See, for example, [WEL 08] and [RAP 13] for a summary of the seminal studies in the field of return predictability.
3 Other methods of utilizing multiple predictive variables include diffusion indices [LUD 07, NEE 13] and multivariate regressions. Refer to [RAP 13] for a comparison of these and other approaches.
4 Refer to [TIM 06] for a summary of literature on combination forecasts.

forecasts are an effective means for allocating between size and value sorted portfolios, in a portfolio selection context. Zhu and Zhu [ZHU 13] employ more sophisticated models and further confirm the effectiveness of the combination forecast approach demonstrating that the technique generates statistical and economic gains over simpler forecasting techniques. To the best of our knowledge, combination forecasts have not been studied across multiasset risk factors.

5.3. Methodology

This section summarizes the research methodology employed in this chapter. It begins by reviewing the predictive regression model employed, followed by the forecast combination methodology. The section then outlines how forecasts are evaluated, and, finally, it will detail how economic significance is measured.

5.3.1. *Predictive regression model*

Following from Kong *et al.* [KON 11] and Rapach *et al.* [RAP 10], a bivariate predictive regression model is specified for each of the risk-factor excess returns:

$$r_{i,t+1} = a_i^j + b_i^j x_t^j + e_{i,t+1}^j \qquad [5.1]$$

where $r_{i,t}$ is the excess return on risk factor i at time t, x_t^j is the predictor variable and $e_{i,t}^j$ is a disturbance term. For each risk factor, j predictive regressions are generated, one for each of the 14 monthly predictive variables from Welch and Goyal [WEL 08]. Out-of-sample forecasts are also generated using a recursive estimation window with an initial in-sample period of m observations, and an out-of-sample period of the final q observations[5]. The first out-of-sample forecast of excess returns on risk factor i is:

$$\hat{r}_{i,m+1}^j = \hat{a}_{i,m}^j + \hat{b}_{i,m}^j x_m^j \qquad [5.2]$$

where $\hat{r}_{i,m+1}^j$ is the out-of-sample forecast of excess returns, and $\hat{a}_{i,m}^j$ and $\hat{b}_{i,m}^j$ are the ordinary least squares estimates of a_i^j and b_i^j, respectively, generated by regressing $\{r_{i,t}\}_{t=2}^{m+1}$ on a constant and $\{x_t^j\}_{t=1}^{m}$. Forecasts for the remaining observations are then generated, calculating a total of $q \times j$ out-of-sample forecasts for each risk factor.

5 Following Rapach *et al.* [RAP 10], the initial in-sample period is set as $m = 60$.

5.3.2. *Forecast combination*

Using the results of the predictive regression models, combination forecasts are formed for each risk factor. The combination forecasts are weighted averages of the j individual forecasts, based on equation [5.1], and are calculated as:

$$\hat{r}_{i,t+1}^{c} = \sum_{j=1}^{J} \omega_{i,t}^{j} \hat{r}_{i,t+1}^{j} \qquad [5.3]$$

where $\hat{r}_{i,t+1}^{c}$ are the combination forecasts and $\omega_{i,t}^{j}$ are the weights calculated at time t.

Following Rapach *et al.* [RAP 10], two classes of weighting schemes are considered. The first class employs simple averaging schemes: mean, median and trimmed mean. The mean combination forecast sets $\omega_{i,t}^{j} = 1/N$ for $j = 1,\ldots, N$ in equation [5.3], the median combination forecast is the median of $\{\hat{r}_{i,t+1}^{j}\}_{j=1}^{N}$ and the trimmed mean combination forecast sets $\omega_{i,t}^{j} = 0$ for the individual forecasts with the smallest and largest values and $\omega_{i,t}^{j} = 1/(N-2)$ for the remaining individual forecasts in equation [5.3].

The second class is the discount mean square prediction error (DMSPE) method of Stock and Watson [STO 04]. Their method adjusts weights based on the historical performance of individual forecasting models using:

$$\omega_{i,t}^{j} = \frac{{\phi_{i,t}^{j}}^{-1}}{\sum_{j=1}^{J} {\phi_{i,t}^{j}}^{-1}}, \qquad [5.4]$$

where

$$\phi_{i,t}^{j} = \sum_{s=m}^{t-1} \theta^{t-1-s} \left(r_{i,s+1} - \hat{r}_{i,s+1}^{j}\right)^2 \qquad [5.5]$$

and θ is a discount factor. This method weights model predictions based on the historical performance of individual forecasting models[6]. The more successful models receive a heavier weighting than the less successful models. When $\theta = 1$, forecasts are not discounted; however, when $\theta < 1$, more recent forecasts are given a heavier weighting than less recent forecasts. Following Rapach *et al.* [RAP 10], $\theta = \{0.9, 1.0\}$ is considered. In summary, a total of five combination weighting

6 Similarly, Carhart *et al.* [CAR 14] propose a dynamic risk-factor timing model that updates estimates based on the statistical fit of previous forecasts.

schemes are analyzed in this chapter: mean, median, trimmed mean, DMSPE $\theta =$ 0.9 and DMPSE $\theta = 1.0$.

5.3.3. *Forecast evaluation*

Many return prediction studies employ sample estimates of the mean of historical returns as a benchmark for evaluating performance. The sample estimates at time *t* are calculated as:

$$\bar{r}_{i,t+1} = \frac{1}{t}\sum_{k=1}^{t} r_{i,k} \quad [5.6]$$

Rapach *et al.* [RAP 10] and Kong *et al.* [KON 11] use equation [5.6] as the basis for statistically evaluating the combination forecasts. Following these studies, the out-of-sample R^2 statistic, R^2_{OS}, suggested by Campbell and Thompson [CAM 08], is employed to compare the sample estimate forecasts and combination forecasts. The R^2_{OS} statistic is calculated as:

$$R^2_{OS} = 1 - \frac{\sum_{k=1}^{q}(r_{i,m+k} - \hat{r}_{i,m+k})^2}{\sum_{k=1}^{q}(r_{i,m+k} - \bar{r}_{i,m+k})^2} \quad [5.7]$$

The statistic measures the reduction in mean square prediction error (MSPE) for the combination forecast relative to the sample estimate forecast. Positive values indicate that the combination forecast has achieved a lower MSPE than the sample estimate. The Clark and West [CLA 07] *MSPE-adjusted* statistic is then used to test whether the R^2_{OS} is statistically greater than zero. This statistic is calculated by first defining:

$$f_{t+1} = (r_{i,t+1} - \bar{r}_{i,t+1})^2 - \left[\left(r_{i,t+1} - \hat{r}_{i,t+1}\right)^2 - \left(\bar{r}_{i,t+1} - \hat{r}_{i,t+1}\right)^2\right] \quad [5.8]$$

and then regressing f_{t+1} on a constant. The *t*-statistic of the constant can then be used in a one-sided hypothesis test with the null hypothesis that the R^2_{OS} statistic is statistically greater than zero tested against the alternative hypothesis:

$$H_0: R^2_{OS} \leq 0$$
$$H_A: R^2_{OS} > 0 \quad [5.9]$$

5.3.4. *Economic significance*

The previous section detailed the statistical tests of the return forecasts; however, the correlation between statistical and economic significance is often weak.

Cenesizoglu and Timmermann [CEN 12] show that only a weak relationship exists between statistical performance and economic significance. Furthermore, as pointed out by Rapach *et al.* [RAP 10], the statistical testing does not account for the risk that is borne by an investor employing the return forecasts in an empirical setting. From the perspective of academia and industry professionals, understanding the difference between statistical and economic significance is critical. This section details the tests employed to examine the economic significance of the economic forecasts.

Following Rapach *et al.* [RAP 10], the average utility of a mean-variance investor with a risk-aversion co-efficient of $\gamma = 3$ is calculated. Noting the diversity of portfolios employed by investors, two investment scenarios are considered. The first allows investment in a single risk factor and the risk-free asset only. The second allows investment in all six risk factors and the risk-free asset. In total, seven portfolio configurations are evaluated.

In constructing the covariance matrix employed in the mean-variance optimization, the analysis follows Kong *et al.* [KON 11], who estimate the covariance matrix using data available from the start of the sample through month t[7]. Using information available at t, the investor allocates to the risk factor(s) using:

$$\widetilde{w}_t = \left(\frac{1}{\gamma}\right)\hat{\Sigma}^{-1}\bar{r}_{t+1} \qquad [5.10]$$

where $\hat{\Sigma}$ is the sample covariance matrix and γ the coefficient of risk-aversion. The investor's average utility is then calculated as:

$$\hat{\upsilon} = \hat{\mu} - \left(\frac{1}{2}\right)\gamma\hat{\sigma}^2 \qquad [5.11]$$

where $\hat{\upsilon}$ is average utility, $\hat{\mu}$ is the average portfolio return and $\hat{\sigma}^2$ is the variance of that return.

To evaluate the economic significance of the combination forecasts, mean-variance portfolios are created using the combination forecasts and the historical average forecasts and the results are compared. Calculating investor utility for each approach, the difference is measured as the gain in utility available to investors who employ the combination forecasts in their portfolio models. By annualizing this

7 Kong *et al.* [KON 11] employ a shrinkage estimator, due to the size of the investment universe, while this chapter employs the sample variance to maintain consistency with the other estimates.

figure, the equivalent management fee an investor would be willing to pay to access these economic forecasts is calculated.

5.4. Data

This chapter employs six US risk factors. Four of the risk factors– market, size, value and momentum – are related to stocks and are grounded in the work of Fama and French [FAM 92] and Carhart [CAR 97]. The remaining two risk factors – credit and term – are related to bonds and are based on the work of Fama and French [FAM 93]. All six risk factors are widely recognized in the investment industry and form the basis of many investment products and processes.

The risk-factor investment proxies in this chapter are sourced from the Kenneth French Website and have been widely employed in the literature[8]. This chapter employs monthly excess returns for the period January 1973 to December 2012 expressed in US dollar terms. More detailed descriptions of the momentum, size, value and market risk-factors are available on the Kenneth French Website. Davis *et al.* [DAV 00] and Fama and French [FAM 93] also provide an in-depth discussion of the portfolio sorting process.

A diverse range of variables have been employed in the predictive literature. Welch and Goyal [WEL 08], for example, employ variables related to stocks, interest rates and the economy. Kao and Shumaker [KAO 99], Levis and Tessaromatis [LEV 04] and L'Her *et al.* [LHE 07] employ similar categories of variables to predict risk-factor (style) returns[9]. Following Rapach *et al.* [RAP 10] and Kong *et al.* [KON 11], and drawing from the literature on risk-factor (style) predictability, we employ the monthly data set of Welch and Goyal [WEL 08] to construct the predictive regressions. Fourteen variables – spanning stock variables, interest rates and economic variables – are used as explanatory variables in the predictive regressions. These variables are described briefly below with further details available in [WEL 08].

– *Dividend-price ratio, D/P*: The difference between the log of dividends and the log of stock prices, where dividends are the 12-month moving sum of dividends paid on the S&P 500 index and price is the price level of the S&P 500 index.

– *Dividend yield, D/Y*: The difference between the log of dividends and the log of lagged stock prices.

8 We acknowledge and thank Ken French for the data used in this chapter. Data were accessed from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

9 For example, earnings–price ratio, book-to-market ratio, default and term spreads, inflation and interest rates.

– *Earnings-price ratio, E/P*: The difference between the log of earnings and the log of stock prices, where earnings are the 12-month moving sum of dividends paid on the S&P 500 index.

– *Dividend payout ratio, D/E*: The difference between the log of dividends and the log of earnings.

– *Book-to-market ratio, B/M*: The ratio of book-value to market value for the Dow Jones Industrial average.

– *Default return spread, DFR*: The difference between the returns on long-term corporate and long-term government bonds.

– *Treasury bill rate, TBL*: The yields on 3-month treasury bills.

– *Long-term bond yield, LTY*: The yields on long-term government bonds.

– *Long-term bond return*, *LTR*: The returns on long-term government bonds.

– *Term spread, TMS*: The difference between the long-term bond yield and the treasury bill rate.

– *Default yield spread, DFY*: The difference between the yields on BAA- and AAA-rated corporate bonds.

– *Stock variance, SVAR*: The sum of squared daily returns on the S&P 500 index.

– *Inflation, INF*: The rate of change of the US Consumer Price Index. Due to the 1-month lag in data releases, the data are lagged 1-month in the predictive regressions.

– *Net equity expansion, NTIS*: The ratio of net issues to market capitalization, where net issues are the 12-month moving sums of net issues by NYSE listed stocks, and market capitalization is the end-of-year market capitalization of NYSE stocks.

Table 5.1 presents the summary statistics for the explanatory variables employed in the predictive regressions. As expected, D/Y and D/P provide similar results due to the close specifications of the variables. All data series are highly non-normal, SVAR, in particular, is highly leptokurtic and positively skewed, due to the episodic periods of relatively extreme volatility; for example, the periods experienced during the financial crisis of 2008 and 1987 stock market crash. D/E also stands out with a high degree of negative skewness that is mostly due to the impact the 2008 financial crisis had on D/E ratios. Testing for normality, the Jarque and Bera [JAR 87] test rejects the null hypothesis of normality at the 1% level for all variables except inflation, which is rejected at the 10% level only.

	Mean	Standard deviation	Skew	Kurtosis	Median	Maximum	Minimum	Jarque-Bera statistic	Jarque-Bera *p*-value
D/P	3.60	0.45	0.12	-1.12	3.55	4.52	2.75	340.40	0.00
D/Y	3.60	0.45	0.13	-1.10	3.55	4.53	2.75	337.98	0.00
E/P	2.81	0.50	0.77	1.73	2.81	4.84	1.90	79.12	0.00
D/E	0.79	0.35	-3.05	14.49	0.85	1.24	-1.38	3388.42	0.00
SVAR	0.00	0.01	9.08	104.07	0.00	0.07	0.00	210905.44	0.00
B/M	0.50	0.30	0.73	-0.80	0.39	1.21	0.12	331.32	0.00
NTIS	0.01	0.02	-0.72	0.43	0.01	0.05	-0.06	173.16	0.00
TBL	0.05	0.03	0.53	0.51	0.05	0.16	0.00	146.73	0.00
LTY	0.07	0.03	0.51	-0.06	0.07	0.15	0.02	207.75	0.00
LTR	0.01	0.03	0.37	2.50	0.01	0.15	-0.11	16.13	0.00
TMS	0.02	0.02	-0.67	0.25	0.02	0.05	-0.04	186.74	0.00
DFY	0.01	0.00	1.65	3.38	0.01	0.03	0.01	220.80	0.00
DFR	0.00	0.01	-0.43	7.87	0.00	0.07	-0.10	488.08	0.00
INF	0.00	0.00	-0.21	3.33	0.00	0.02	-0.02	5.71	0.06

This table presents the summary statistics of the explanatory variables employed in the predictive regressions used in this chapter. Following Rapach *et al.* [RAP 10] and Kong *et al.* [KON 11], these are the 14 monthly explanatory variables described in [WEL 08].

Table 5.1. *Summary statistics for explanatory variables, December 1972–December 2012*

5.5. Results

5.5.1. *Single economic variable forecasts*

5.5.1.1. *Forecasting errors*

Figure 5.1 compares the cumulative differences in errors produced by the economic variable forecasts and the sample estimate forecasts. Where the line slopes upwards and to the right, the economic variable is generating a smaller forecast error than the historical average forecast for the specified risk factor, that is the economic forecast is deemed more accurate. Figure 5.1 shows that no single economic variable consistently outperforms its historical average forecasts. Consistent with the results of Rapach *et al.* [RAP 10] and Kong *et al.* [KON 11], the forecasts based on single economic variables do not consistently generate smaller errors than the historical average forecasts. This is not just for the market risk factor, but all six of the risk factors. The figure shows that there are short periods where the competing forecasts diverge in terms of performance; however, this is generally due to the economic variable forecast underperforming; for example, the SVAR variable during the stock market crash of 1987. The figure indicates that no single economic variable consistently produces more accurate risk-factor forecasts than those based on historical average returns data.

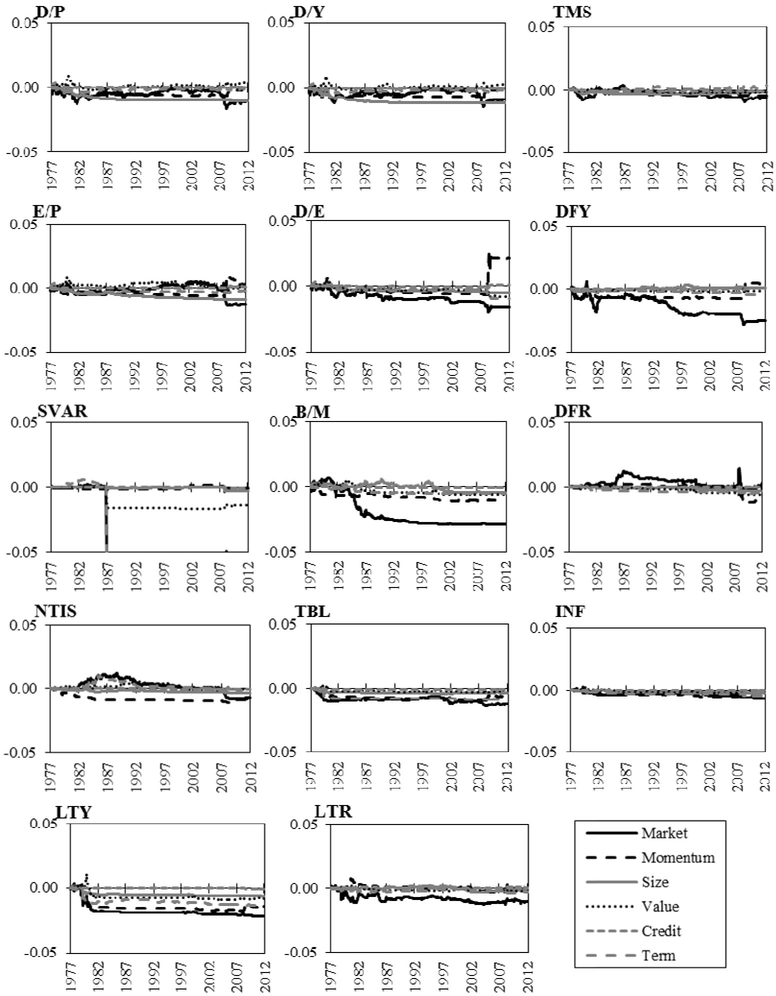


Figure 5.1. *Cumulative forecast error differentials: single economic variables and historical average forecasts*

NOTE.– Figure 5.1 compares the performance of the single economic variable regression and sample estimate forecasts of the six US risk factors: market, momentum, value, size, term and credit. Specifically, these are the cumulative square prediction errors of the sample estimate forecasts minus the cumulative square prediction errors of the single economic variable regression models for the period from December 1977 to December 2012. An increasing line indicates better performance for the single economic variable regression models; a decreasing line indicates better performance for the sample estimate model. Each chart represents one of the 14 economic variables, while each line represents the performance for a single risk-factor investment.

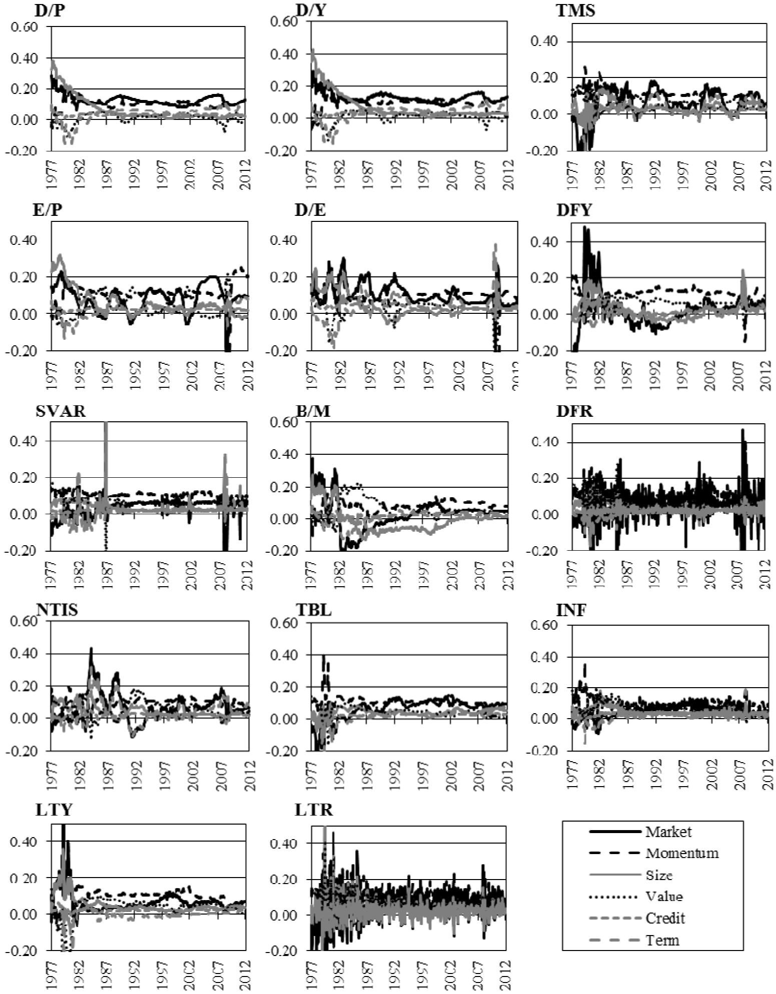


Figure 5.2. *Risk factor annualized excess return forecasts: single economic variable forecasts*

NOTE.– Figure 5.2 illustrates the time series of annualized excess return forecasts of the six US risk factors: market, momentum, value, size, term and credit. Forecasts are estimated using the individual economic variable models for the period from December 1977 to December 2012. Specifically, the forecasts are the out-of-sample estimates of the single economic variable regression models. Each forecast is the 1-month-ahead annualized excess return estimate produced by the models. Each chart represents the forecasts produced by each of the economic variables.

5.5.1.2. *Forecast returns*

Figure 5.2 illustrates the annualized excess return forecasts for all six risk factors estimated using each of the individual economic variable models. The figure shows that return forecasts can vary across wide and unrealistic ranges. The SVAR variable, for example, produces some of the more egregious forecasts, up to 298% per annum for the market risk factor during the stock market crash of October 1987, which is the most volatile period in the data sample. As shown in Rapach *et al.* [RAP 10], return forecasts can also be erratic, changing significantly from one month to the next, particularly for the more volatile economic variables, such as LTR and DFR. While single economic variables generally produce reasonable forecasts of risk-factor excess returns, they can be volatile and unrealistic for extended periods of time.

Variable	Market	Momentum	Size	Value	Credit	Term
D/P	-1.19	-0.19	-2.47	0.54 ***	-0.93	-0.26
D/Y	-1.03	-0.12	-2.93	0.49 ***	-0.78	-0.39
E/P	-1.41	0.06	-2.23	-0.07	1.67 *	-0.60
D/E	-1.79	2.36 *	-1.33	-1.96	1.80 **	-2.17
SVAR	-6.14	-0.11	-0.72	-3.56	-1.42	-13.66
B/M	-3.25	-1.10	-1.11	-1.48	-1.38	-1.21
NTIS	-0.85	-0.97	-0.83	-0.21	-1.22	-0.32
TBL	-1.41	-0.66	-0.95	-0.53	-1.94	-1.96
LTY	-2.43	-1.52	-1.53	-2.01	-1.05	-3.31
LTR	-1.18	0.10 *	-0.35	-0.63	0.67 *	-0.65
TMS	-0.78	-0.48	-0.45	-0.39	-1.20	0.91 *
DFY	-2.83	0.49	0.16 *	-0.45	1.36 **	-1.05
DFR	0.07	-1.38	-0.78	-1.47	-0.87	-1.04
INF	-0.78	-0.64	-0.61	-0.05	0.71 *	-1.15

This table presents out-of-sample results for the single economic variable forecasts for the period December 1977 to December 2012. The Campbell and Thompson [CAM 08] R^2 statistic measures out-of-sample performance. The statistic corresponds to a one-sided test of the null hypothesis that the single economic variable forecast model has equal expected square prediction error relative to the historical average forecast model against the alternative hypothesis that the single economic variable forecast model has a lower expected square prediction error than the historical average forecast model. P-values are calculated using the Clark and West's [CLA 07] MSPE-adjusted statistic. *, ** and *** denote statistical significance at the 10, 5, and 1% levels, respectively.

Table 5.2. *Single economic variable forecast statistical results*

5.5.1.3. *Statistical significance*

Table 5.2 evaluates the statistical performance of the single variable forecast models. Following the results of Rapach *et al.* [RAP 10], very few of the individual variable models are statistically significant. Some variables work for one or two risk factors, but never more than two. Eleven of the forecasts produce statistically significant R^2 values; however, the majority of these are significant at the 10% level only. Interestingly, none of the significant forecast results are for the market risk factor. D/P and the closely related D/Y variable are significant at the 1% level for the value risk factor, while five variables are significant for the credit risk factor. The term and size risk factors report one significant forecast each and the momentum risk factor has two variables that provide significant forecasts. Overall, these results suggest that single variable forecasts are poor predictors of risk-factor returns.

	Market	Mom.	Size	Value	Credit	Term	Diversified
D/P	-0.84	-1.40	-2.06	0.01	0.46	-8.81	-66.47
D/Y	-0.31	-1.05	-2.42	-0.05	0.25	-8.71	-69.20
E/P	-1.53	0.78	-2.12	-2.25	-5.23	-7.47	-48.67
D/E	-2.88	-11.31	-1.57	-6.76	-23.45	-14.68	-102.60
SVAR	-17.88	2.98	-1.41	-9.17	-7.07	-4.83	-27.48
B/M	-5.25	-4.68	-2.48	-1.77	-0.87	-3.84	-28.74
NTIS	-0.38	-2.74	-1.10	-1.78	1.10	-4.72	-5.98
TBL	-1.78	-6.11	-1.23	-1.20	-1.64	-45.56	-69.70
LTY	-5.12	-9.54	-2.41	-6.88	0.23	-33.51	-103.04
LTR	-1.74	-0.53	0.38	-0.39	-11.86	-6.78	-6.71
TMS	-0.93	-2.19	0.02	-1.53	-2.25	-16.92	-23.39
DFY	-4.79	2.10	1.28	-0.14	-17.47	-3.31	-20.28
DFR	-3.57	-3.47	-2.51	-4.08	-14.36	-2.89	-28.23
INF	-1.49	-3.06	-0.62	-0.18	-2.47	-8.55	-10.38
Average	-3.46	-2.87	-1.30	-2.58	-6.05	-12.18	-43.63

This table reports utility gains for an investor employing the single economic variable forecasts rather than the sample estimate forecasts for the out-of-sample period from December 1977 to December 2012. The details and abbreviations for the variables are summarized in section 5.4. The utility gain is the equivalent annual fee that a mean-variance investor with a risk-aversion co-efficient of 3 would be willing to pay to employ the forecast model. The average denotes the arithmetic average of utility gains across economic variable models for each risk-factor investment. Negative numbers indicate that the economic variable model reduces utility relative to the sample estimate forecast model.

Table 5.3. *Investor utility (γ = 3) for single economic variable forecasts*

5.5.1.4. *Economic significance*

Table 5.3 reports the economic significance of the single economic variable forecast models. Economic significance is measured as the utility gains achieved by investors employing the single economic variable forecasts rather than the sample estimate forecasts, applied in the mean-variance portfolio process. Forecast results are reported for seven portfolios: six which invest in each of the risk factors individually, and one diversified portfolio that invests in all six risk factors. Following from the work of Rapach *et al.* [RAP 10], the table reports that the single economic variable models consistently underperform the sample estimate forecasts, achieving lower levels of utility, on average, in the majority of cases. The single economic variable forecasts are particularly ineffective when employed in a diversified portfolio. In this context, economic forecasts result in utility losses of 43.63% a year when compared to the historical average forecasts. Overall, the findings in Table 5.3 suggest that single variable forecast models are poor and provide little or no level of predictability that is of economic significance.

5.5.2. *Combination forecasts*

5.5.2.1. *Forecasting errors*

This section reviews the results of the combination forecasts. Figure 5.3 compares the risk-factor excess return forecasts produced by the combination and historical average models. In contrast to the models based on a single economic variable, the combination forecasts appear to be more effective at forecasting the risk factors. Although the single economic variable models generally report larger errors than the sample estimate forecasts, the combination models generate distinctly smaller errors, or, at worst, offer performance similar to the sample estimate forecasts. The return forecasts of the momentum risk factor appear to be the exception; however, with the combination models performing poorly for the majority of the out-of-sample period.

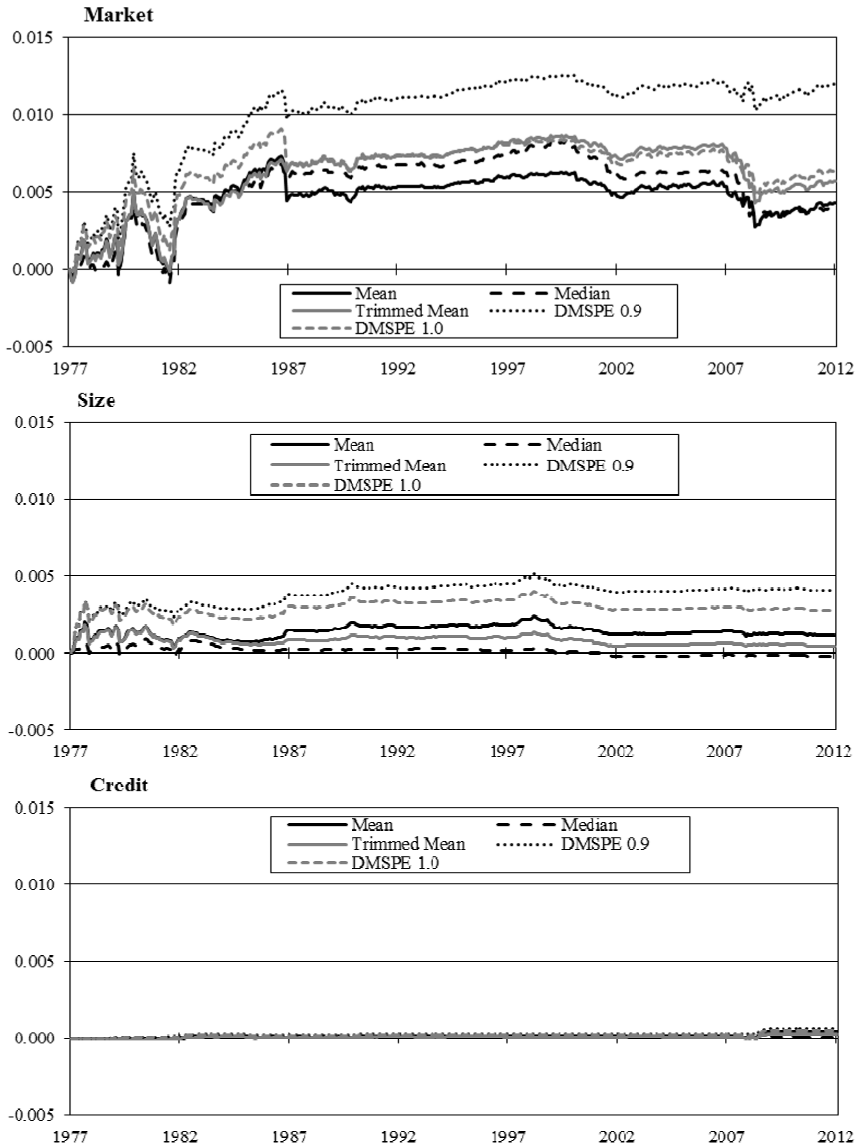
Examining each of the risk factors, it can be seen that the market risk factor exhibits the largest differential in the size of the MSPE over the sample estimate model, a result consistent with the findings in [RAP 10]. This is not unexpected given the predictive variables were derived from the equity market forecasting literature. The results are reasonably consistent across the five different weighting schemes although the DMSPE where $\theta = 0.9$ appears to exhibit the best performance relative to the sample estimate forecasts.

It is apparent from Figure 5.3 that the performance of the combination forecasts of the market risk factor varies over the data sample. From the beginning of the sample in 1977 until the stock market crash of October 1987, the combination forecasts strongly outperform the historical average model by producing lower forecast errors. While the performance of the combination models appears strong, they are occasionally erratic, with short periods of poor performance often followed by very strong performance. These large swings in performance appear to become less frequent as the size of the in-sample period grows over time. After 1987, the performance of the combination forecasts moderates, although the figure suggests performance is still better than the historical average models. The performance of the combination models deteriorates during the GFC; however, it recovers somewhat after the nadir of the crisis.

Along with market, the size and value risk factors also appear to exhibit lower forecast errors when the combination techniques are used. This is consistent with the results of Kong *et al.* [KON 11] who find that forecasts improve for small capitalization and high-value stocks. Their results, however, are based on long-only stock portfolios that exhibit exposure to the market risk factor as well as the size and value risk factors. In contrast, the results presented here are based on portfolios that are long high-value (small-capitalization) stocks and short low-value (large-capitalization) stocks. In theory, the portfolios employed should have only minimal market exposure. The results suggest that the forecasts of size and value may not be as effective as forecasts of the market risk factor, which is an issue explored in the following sections of this chapter.

In contrast to the results for the equity-based risk factors, the findings for the bond-based risk factors, credit and term, appear to be less compelling. Compared to the other risk factors (in particular the market risk factor), the credit and term risk factors do not exhibit large performance differences to the historical average forecast models. Figure 5.3 also suggests that the combination forecasts are the least effective for the momentum risk factor. The forecast errors for this risk factor, generated by the combination models, appear to be no better than the sample estimate forecasts for the majority of the sample period.

In summary, Figure 5.3 indicates that the combination forecasts, in general, offer more effective forecasts than the single variable models. The effectiveness of the forecasts, as evaluated by the size of the forecast errors, appears to vary over time and across risk factors. These points will be formally evaluated statistically and economically in the following section.


Market
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0.010
0.005
0.000
-0.005
1977
1982
1987
1992
1997
2002
2007
2012
Mean
Median
Trimmed Mean
DMSPE 0.9
DMSPE 1.0
Size
0.015
0.010
0.005
0.000
-0.005
1977
1982
1987
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1997
2002
2007
2012
Mean
Median
Trimmed Mean
DMSPE 0.9
DMSPE 1.0
Credit
0.015
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1977
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Mean
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DMSPE 1.0

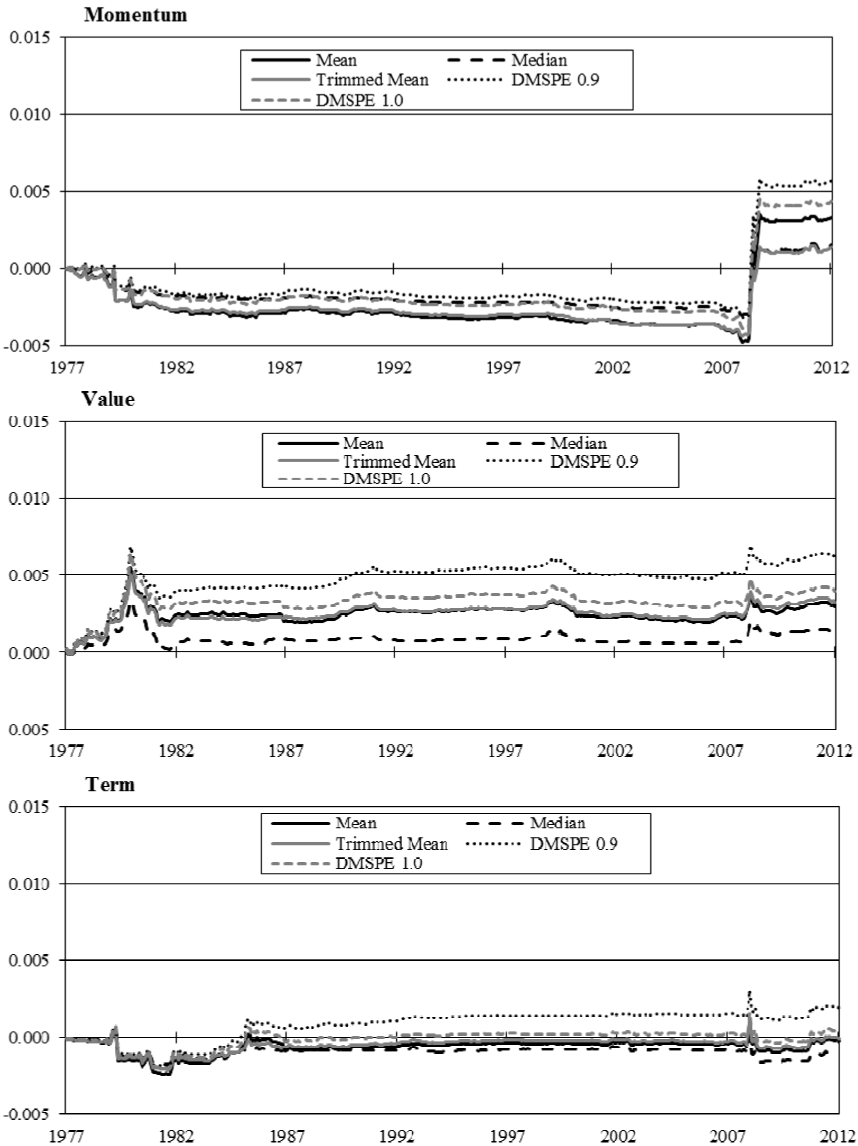


Figure 5.3. *Cumulative forecast error differentials: combination and historical average forecasts*

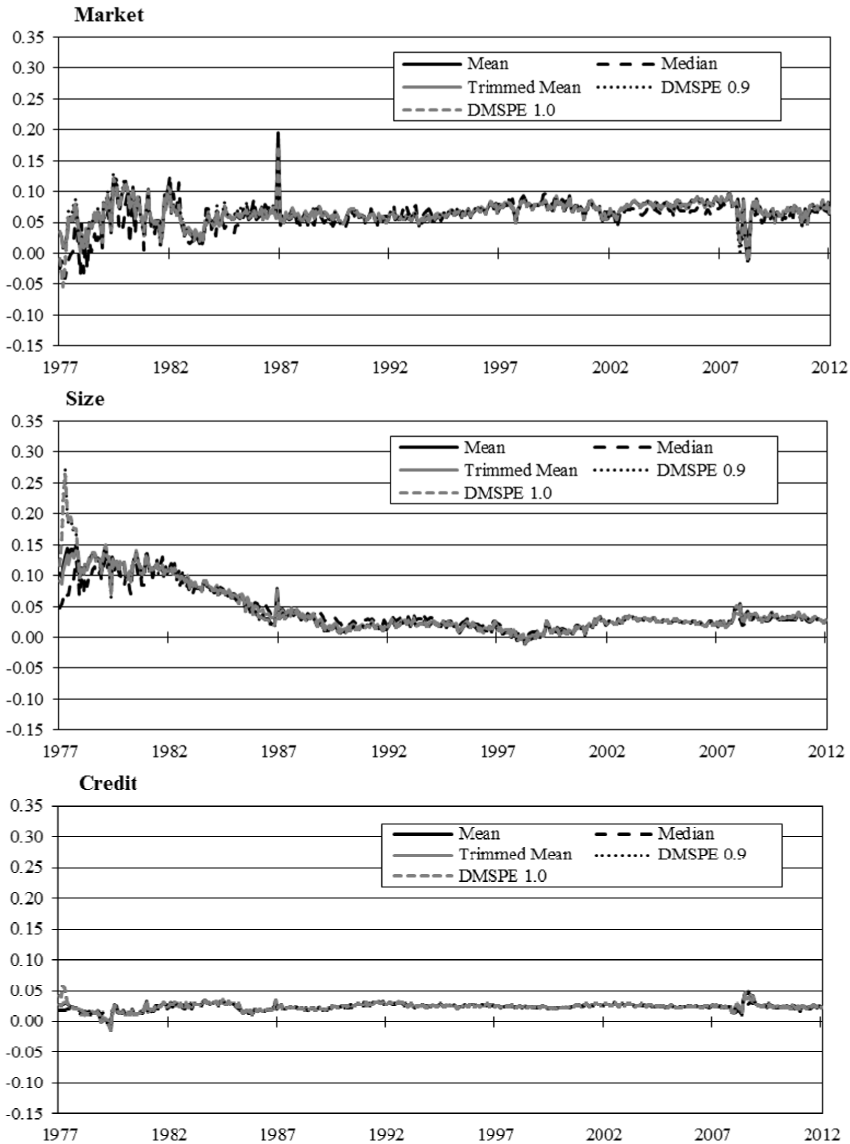
Figure 5.3 compares the performance of the combination and sample estimate forecasts. Specifically, these are the cumulative square prediction errors of the sample estimate forecasts minus the cumulative square prediction errors of the combination models for the period December 1977 to December 2012. An increasing line indicates better performance for the combination models; a decreasing line indicates better performance for the sample estimate model. Each chart shows the model performance for each risk factor, while each line represents the performance of the different weighting schemes used in the combination forecasts.

5.5.2.2. *Forecast returns*

Figure 5.4 illustrates the annualized risk-factor excess return forecasts provided by the combination forecast models. In comparison to the single variable forecasts (see Figure 5.2), a number of features are apparent. First, the combination forecasts appear more stable than the individual forecasts. While the combination forecasts exhibit occasional sudden changes, these are rare, particularly in comparison to the single variable return forecasts. Second, the ranges of return forecasts are much more realistic, with the most optimistic forecasts rarely above 20% and the most pessimistic rarely below –5%. In fact, many of the more extreme forecasts occur in the early part of the sample where the in-sample window is the smallest. These findings corroborate the analysis of Rapach *et al.* [RAP 10], which examines the market factor only, as well as advancing their work by finding similar results across other risk factors. Unlike the single variable models, the combination models rarely produce negative return forecasts, particularly in the latter part of the sample.

Table 5.4 compares the mean and standard deviations of the single variable and combination return forecasts. On average, the single variable and combination models estimate similar expected return forecasts. Despite these similarities, stark differences in the variability of the outputs are revealed when the standard deviations of the different approaches are compared. The combination models exhibit the lowest standard deviation of all forecasting models for the market, momentum, value and credit risk factors. Rapach *et al.* [RAP 10] note that by construction, the combination forecasts smooth out some of the variability present in the single variable forecasts. This is clearly seen when comparing the standard deviation of the combination and single variable forecasts. All of the combination model forecasts exhibit standard deviations below the average of the single variable model forecasts.

This figure illustrates the time series of annualized excess return forecasts of the six risk factors. Forecasts are estimated using the combination forecast models for the period of December 1977 to December 2012. Specifically, the forecasts are the out-of-sample estimates of the combination forecast models. Each forecast is the 1-month-ahead annualized excess return estimate produced by the models. Each chart represents the forecasts of each risk factor based on the five different weighting schemes.


Market
Mean
Median
Trimmed Mean
DMSPE 0.9
DMSPE 1.0
0.35
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DMSPE 0.9
DMSPE 1.0
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DMSPE 1.0
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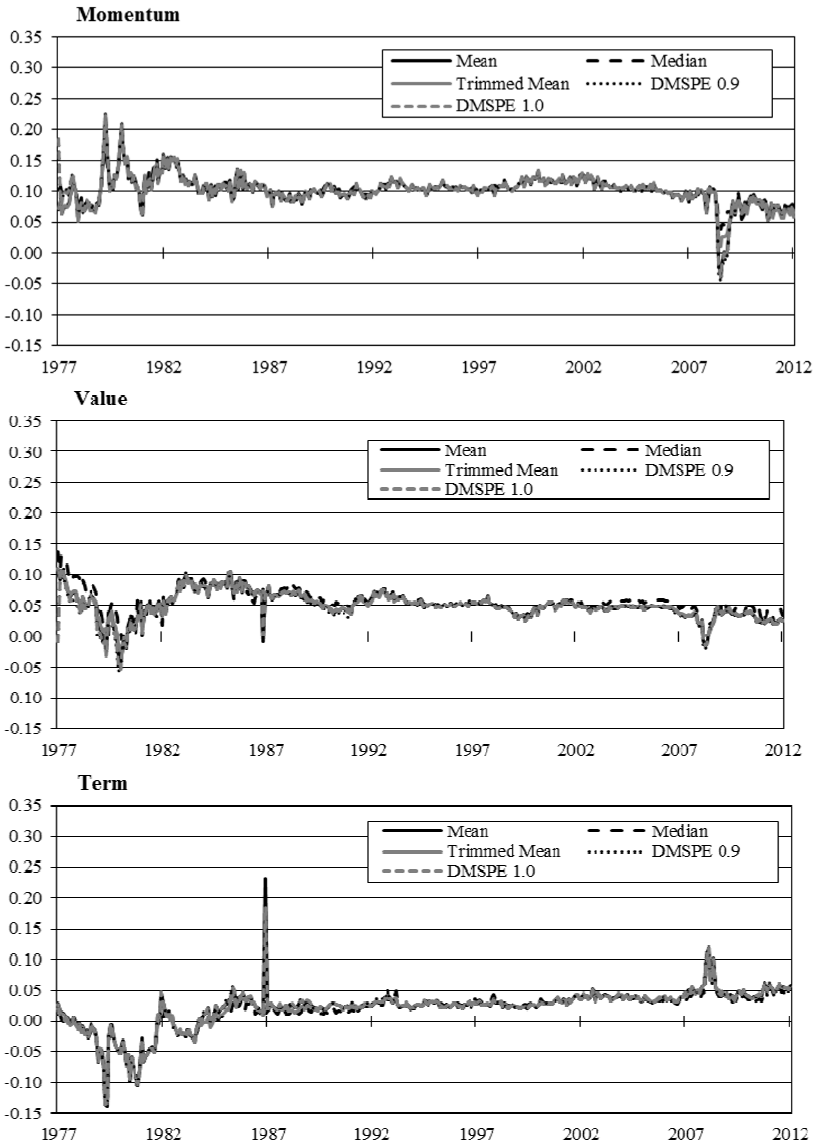

Figure 5.4. *Risk factor annualized excess return forecasts: combination forecasts*

	Mean						Standard Deviation					
	Market	Mom.	Size	Value	Credit	Term	Market	Mom.	Size	Value	Credit	Term
Panel A: Return Forecasts based on Individual Economic Variables												
D/P	12.95	9.58	6.48	0.83	3.20	4.13	3.46	3.64	8.15	3.36	0.70	4.67
D/Y	12.96	9.28	7.14	0.91	3.17	3.77	3.47	3.81	8.52	3.28	0.68	4.75
E/P	7.91	11.04	6.02	3.82	2.17	1.81	7.64	6.03	7.08	5.73	1.47	3.66
D/E	10.52	8.97	4.39	3.59	3.76	3.82	5.95	10.84	6.28	5.31	2.10	6.03
SVAR	3.77	10.76	3.90	6.47	2.26	2.32	11.80	2.97	4.01	6.63	0.99	15.11
B/M	2.96	8.35	-0.69	6.87	2.13	1.62	10.02	3.39	7.83	5.82	1.16	3.87
NTIS	6.50	9.92	4.09	5.57	2.06	3.92	8.69	3.22	3.63	5.03	0.97	7.40
TBL	6.10	10.34	4.28	4.94	2.00	1.54	6.55	4.22	2.28	3.46	1.87	4.60
LTY	6.72	9.72	5.02	3.49	2.16	-0.37	6.29	4.69	4.64	7.02	0.81	3.57
LTR	4.27	10.62	3.78	7.02	2.33	1.61	9.91	6.37	5.75	4.00	2.02	4.63
TMS	5.90	11.49	4.03	5.97	2.26	3.04	7.95	3.01	3.48	3.15	1.51	5.28
DFY	2.61	11.03	2.59	6.77	1.97	1.07	10.27	4.00	5.45	2.72	2.00	2.83
DFR	3.73	10.85	3.69	6.98	2.31	1.33	8.42	5.76	2.92	3.74	1.50	2.81
INF	5.03	10.82	4.34	7.08	2.86	1.95	3.99	3.34	2.85	3.38	1.21	3.25
Average	6.57	10.20	4.22	5.02	2.48	2.25	7.46	4.66	5.20	4.47	1.36	5.17
Panel B: Return Forecasts based on Combination Forecasts												
Mean	6.57	10.20	4.22	5.02	2.48	2.25	1.91	2.45	3.79	2.20	0.59	3.26
Median	6.14	10.49	4.24	5.66	2.43	1.91	2.28	1.89	3.07	2.07	0.46	2.96
Trimmed Mean	6.63	10.25	4.36	5.07	2.49	2.12	1.62	2.23	3.65	2.01	0.52	3.05
DMSPE θ=0.9	6.61	10.26	4.29	4.92	2.50	2.24	2.06	2.54	4.18	2.30	0.67	3.13
DMSPE θ=1.0	6.57	10.27	4.33	4.94	2.49	2.24	2.05	2.47	4.22	2.29	0.66	3.21
Average	6.50	10.29	4.29	5.12	2.47	2.15	1.98	2.31	3.78	2.17	0.58	3.12

This table reports the means and standard deviations of the annualized excess return forecasts for the six risk factors. Results are for the out-of-sample period December 1977 to December 2012. Panel A reports statistics for the 14 individual economic variable forecasts. The details and abbreviations for the variables are summarized in section 5.4. Panel B reports the statistics for the five combination forecasts.

Table 5.4. *Return forecast summary statistics*

Weighting Scheme	Market	Mom.	Size	Value	Credit	Term
Mean	0.48 *	0.37	0.29	0.76 **	0.97 **	-0.05
Median	0.44 *	0.17	-0.04	0.34	0.25	-0.24
Trimmed Mean	0.64 **	0.16	0.11	0.84 **	0.68 **	-0.02
DMSPE θ=0.9	1.34 ***	0.64	1.01 ***	1.57 ***	1.49 ***	0.46
DMSPE θ=1.0	0.71 **	0.48	0.68 **	1.01 **	1.16 ***	0.09

This table presents out-of-sample results for the five combination forecasting techniques for the period December 1977 to December 2012. The Campbell and Thompson [CAM 08] R^2 statistic is employed to measure out-of-sample performance. The statistic corresponds to a one-sided test of the null hypothesis that the combination forecast model has equal expected square prediction error relative to the historical average forecast model against the alternative hypothesis that the combination forecast model has a lower expected square prediction error than the historical average forecast model. *P*-values are calculated using the Clark and West's [CLA 07] MSPE-adjusted statistic. *, ** and *** denote statistical significance at the 10, 5 and 1% levels, respectively.

Table 5.5. *Combination forecast statistical results*

5.5.2.3. *Statistical significance*

Table 5.5 shows that the combination models produce more accurate return forecasts than the single variable models. Unlike the results reported for the single variable models (see Table 5.2), which are rarely significant, many of the combination models produce statistically significant results. Confirming the results of Rapach *et al.* [RAP 10] and Kong *et al.* [KON 11], the findings show that the combination forecasts are effective for the market risk factor where all the weighting techniques are statistically significant at the 10% level. In contrast, none of the single variable model forecasts, reported earlier, were significant for the market risk factor. The two DMPSE weighting schemes report the highest values for the R^2 statistic, 1.34% for $\theta = 0.9$ and 0.71% for $\theta = 1.0$. Importantly, the results show that combination forecasts are effective for other risk factors as well.

The combination models provide statistically significant forecasts for the size, credit and value risk factors. Furthermore, the combination models appear to be more effective for the value and credit risk factors than the market risk factor. For the value and credit risk factors, the combination forecasts produce R^2 values that are higher than the market risk factor for four of the five weighting techniques. The results support the findings of Kong *et al.* [KON 11] who demonstrate that combination portfolios perform better for high-value stock portfolios than for low-value stock portfolios. Interestingly, the combination forecasts perform very well for the credit risk factor, despite the modest results shown in Figure 5.3. Two weighting schemes for the credit risk factor are significant at the 5% level, while another two are significant at the 1% level. Although the economic variables were originally specified to forecast the market premium, the tests provide evidence that they are more effective at forecasting the credit premium[10].

Despite appearing to exhibit smaller forecasting errors than the sample estimate forecasts in Figure 5.3, the combination forecasts offer only modest success in forecasting the returns of the size risk factor. Only the two DMSPE weighting techniques achieve statistically significant R^2 values. Two other techniques achieve positive R^2 statistics; however, these are not significant at the standard significance levels. At first, this result seems inconsistent with those of Kong *et al.* [KON 11], who find the performance of combination forecasts improves as market capitalization decreases. The results here, however, are based on the size risk factor (created from long and short positions in size portfolios) rather than long-only size portfolios, leading to differences in the results. While the results lack statistical significance, four of five weighting techniques offer positive R^2 values. That is, forecasting ability may increase as market capitalization decreases; however, when the size risk factor is isolated, the effectiveness of the forecasts decreases.

The combination models offer very limited forecasting performance for the term and momentum risk factors. While the combination models for the momentum risk factor achieve positive R^2 statistics, they are not significant at the usual levels. The statistical results for the term risk factor are the weakest. Of the five weighting techniques, only two achieve R^2 values greater than zero.

As well as varying across risk factors, the performance of the combination forecasts differs across weighting techniques. The DMSPE weighting schemes are the most effective of the five approaches examined. These weighting techniques achieve positive R^2 values for all risk-factor forecasting models, and in eight of 12 DMSPE models the results are statistically significant at the 5 or 1% levels. By including an intertemporal discounting factor, that is, by setting the parameter θ below unity, the R^2 statistic for all risk-factor forecasts improves. In the case of the market risk factor, the improvement is 0.63 percentage points. The weighting approach employed to combine forecasts impacts on statistical performance.

Overall, the evidence presented in this chapter builds on the existing literature by demonstrating that combination models offer statistically significant forecasts for the value, credit, size and market risk factors. The forecasts for the term and momentum risk factors, however, lack statistical significance. It is also apparent that results vary between the different combination weighting techniques employed in the chapter.

10 The relationship between the credit and market risk-factor is a complex one. It is examined in [MER 74], [CHE 86], [FAM 93] and [BHA 10] among others.

5.5.2.4. *Economic significance*

This section measures the economic significance of the combination forecasts when employed in the risk-factor framework. Table 5.6 presents the utility gains for investors employing combination forecasts relative to historical average forecasts in the mean-variance framework. The results suggest that the combination model forecasts produce economically significant results when employed in the mean-variance framework[11]. Unlike the single economic variable models, the majority of combination models produce gains in utility. The models are most useful for the market, momentum, size, value and credit risk-factor portfolios that achieve utility gains for almost all forecast models. The annual utility gains for these five risk factors ranges from an average of 0.69% for the momentum risk factor to 1.91% for the value risk factor. These values are the equivalent annual management fees an investor would be willing to pay to use the combination forecasts. When applied to the term risk factor and diversified portfolios, portfolio performance is poor. While outperforming the single variable forecasts, on average, they result in a lower level of utility than that achieved with the sample estimate forecasts. These results are consistent with the previously reported statistical tests, which show that the effectiveness of combination forecasts varies across risk factors. On balance, the evidence suggests that the economic significance of combination forecasts of risk factors provide the potential for utility gains for mean-variance investors; however, results vary across risk factors, and single and multirisk factor portfolios.

Weighting Scheme	Market	Mom.	Size	Value	Credit	Term	Diversified
Mean	1.01	0.71	1.11	1.54	0.60	-6.10	-13.09
Median	0.67	0.26	0.27	1.06	0.57	-5.47	-9.19
Trimmed Mean	1.25	-0.08	0.72	1.77	0.39	-5.39	-12.14
DMSPE θ=0.9	2.62	1.48	2.50	3.19	1.79	-4.69	-7.68
DMSPE θ=1.0	1.41	1.11	1.88	2.01	1.02	-5.37	-12.72
Average	1.39	0.69	1.29	1.91	0.87	-5.40	-10.96

This table reports utility gains for investors employing combination forecasting techniques rather than sample estimate forecasts for the out-of-sample period from December 1977 to December 2012. The table reports results for each of the five combination forecast weighting techniques. The utility gain is the equivalent annual fee that a mean-variance investor with a risk-aversion co-efficient of 3 would be willing to pay to employ the forecast model. The average is the arithmetic average of utility gains across combination forecast models for each risk-factor investment. Negative numbers indicate that the economic variable model reduces utility relative to the sample estimate forecast model.

Table 5.6. *Comparison of investor utility (γ = 3) for combination forecast models*

11 Results for $\gamma = 1$ and 5 are consistent with those reported here where $\gamma = 3$. The results are available upon request.

5.6. Conclusion

While debate continues on the effectiveness of equity market forecasting models, recent studies have shown that statistical and economically significant forecasts can be constructed by combining the outputs of economic models. This research provides a fertile ground for equity and traditional asset managers; however, managers interested in considering the risk-factor framework have little research to help guide their investment decision making processes. This chapter contributes to the literature by demonstrating that the combination forecast approach of Rapach *et al.* [RAP 10] is effective, to varying degrees, within the risk-factor framework.

This chapter provides evidence that combination forecasts of risk-factor returns are statistically significant. Specifically, evidence of statistical significance in four of the six risk factors is found. Although economic variables selected to forecast equity market returns are employed, these variables are more effective at forecasting the credit and value risk factors. Furthermore, the effectiveness of forecasts varies across risk factors and combination weighting techniques.

When combination forecasts are employed in the mean-variance framework, they achieve utility gains over models that employ sample estimates. The analysis reveals evidence that combination forecasts for five of the six risk factors offer utility gains over sample-based forecasts. While the combination forecasts are generally effective for single risk-factor portfolios, they are less effective for multirisk factor portfolios. When employed in a multirisk factor context, there is a dramatic decrease in the effectiveness of the combination forecasts. These results should be considered as a caution to investors considering the application of the combination forecast technique when developing risk-factor portfolios.

Viewing investment portfolios from the perspective of risk factors has attracted the attention of academics and practitioners. While much is known about the effectiveness, or otherwise, of equity market forecasts, little is known about the effectiveness of risk factor forecasts. For the first time, this chapter documents evidence that opportunities exist for the application of combination forecasts in the risk factor framework. The results, however, vary across risk factors and combination weighting techniques, suggesting a challenging environment for investors considering the application of such models.

5.7. Bibliography

[AHM 02] AHMED P., LOCKWOOD L.J., NANDA S., "Multistyle rotation strategies", *The Journal of Portfolio Management*, vol. 28, no. 3, pp. 17–29, 2002.

[ARN 16] ARNOTT R.D., BECK N., KALESNIK V., "Timing "Smart Beta" Strategies? Of Course! Buy Low, Sell High!", *Research Affiliates*, available online, September 2016.

[ARN 17] ARNOTT R.D., BECK N., KALESNIK V., "Forecasting Factor and Smart Beta Returns", *Research Affiliates*, available online, February 2017.

[ASN 00] ASNESS C.S., FRIEDMAN J.A., KRAIL R.J. *et al.*, "Style timing: value versus growth", *Journal of Portfolio Management*, vol. 26, no. 3, pp. 50–60, 2000.

[ASN 17] ASNESS C.S., CHANDRA S., ILMANEN A. *et al.*, "Contrarian factor timing is deceptively difficult", *Journal of Portfolio Management*, vol. 43, no. 5, pp. 72–87, 2017.

[BHA 10] BHAMRA H.S., KUEHN L.-A., STREBULAEV I.A., "The levered equity risk premium and credit spreads: a unified framework", *The Review of Financial Studies*, vol. 23, no. 2, pp. 645–703, 2010.

[CAM 08] CAMPBELL J.Y., THOMPSON S.B., "Predicting excess stock returns out of sample: can anything beat the historical average?", *The Review of Financial Studies*, vol. 21, no. 4, pp. 1509–1531, 2008.

[CAR 97] CARHART M.M., "On persistence in mutual fund performance", *Journal of Finance*, vol. 52, no. 1, pp. 57–82, 1997.

[CAR 14] CARHART M., CHEAH U.-W., DE SANTIS G. *et al.*, "Exotic beta revisited", *Financial Analysts Journal*, vol. 70, no. 5, pp. 24–52, 2014.

[CEN 12] CENESIZOGLU T., TIMMERMANN A., "Do return prediction models add economic value?", *Journal of Banking & Finance*, vol. 36, no. 11, pp. 2974–2987, 2012.

[CHE 86] CHEN N.-F., ROLL R., ROSS S.A., "Economic forces and the stock market", *The Journal of Business*, vol. 59, no. 3, pp. 383–403, 1986.

[CLA 07] CLARK T.E., WEST K.D., "Approximately normal tests for equal predictive accuracy in nested models", *Journal of Econometrics*, vol. 138, no. 1, pp. 291–311, 2007.

[DAV 00] DAVIS J.L., FAMA E.F., FRENCH K.R., "Characteristics, covariances, and average returns: 1929 to 1997", *Journal of Finance*, vol. 55, no. 1, pp. 389–406, 2000.

[FAM 92] FAMA E.F., FRENCH K.R., "The cross-section of expected stock returns", *Journal of Finance*, vol. 47, no. 2, pp. 427–465, 1992.

[FAM 93] FAMA E.F., FRENCH K.R., "Common risk factors in the returns on stocks and bonds", *Journal of Financial Economics*, vol. 33, no. 1, pp. 3–56, 1993.

[JAR 87] JARQUE C.M., BERA A.K., "A test for normality of observations and regression residuals", *International Statistical Review*, vol. 55, no. 2, pp. 163–172, 1987.

[KAO 99] KAO D.-L., SHUMAKER R.D., "Equity style timing", *Financial Analysts Journal*, vol. 55, no. 1, pp. 37–48, 1999.

[KON 11] KONG A., RAPACH D.E., STRAUSS J.K. *et al.*, "Predicting market components out of sample: asset allocation implications", *The Journal of Portfolio Management*, vol. 37, no. 4, pp. 29–41, 2011.

[LHE 07] L'HER J.-F., MOUAKHAR T., ROBERGE M., "Timing small versus large stocks", *The Journal of Portfolio Management*, vol. 34, no. 1, pp. 41–50, 2007.

[LEV 04] LEVIS M., TESSAROMATIS N., "Style rotation strategies", *The Journal of Portfolio Management*, vol. 30, no. 4, pp. 160–169, 2004.

[MAR 52] MARKOWITZ H., "Portfolio selection", *Journal of Finance*, vol. 7, no. 1, pp. 77–91, 1952.

[MER 74] MERTON R., "On the pricing of corporate debt: the risk structure of interest rates", *Journal of Finance*, vol. 29, no. 2, pp. 449–470, 1974.

[RAP 10] RAPACH D.E., STRAUSS J.K., ZHOU G., "Out-of-sample equity premium prediction: combination forecasts and links to the real economy", *Review of Financial Studies*, vol. 23, no. 2, pp. 821–862, 2010.

[RAP 13] RAPACH D.E., ZHOU G., "Forecasting stock returns", in ELLIOTT G., TIMMERMANN A. (eds.), *Handbook of Economic Forecasting*, vol. 2, Elsevier, Amsterdam, 2013.

[STO 04] STOCK J.H., WATSON M.W., "Combination forecasts of output growth in a seven-country data set", *Journal of Forecasting*, vol. 23, no. 6, p. 405, 2004.

[TIM 06] TIMMERMANN A., "Forecast combinations", in ELLIOTT G., GRANGER C.W.J., TIMMERMANN A. (eds.), *Handbook of Economic Forecasting*, vol. 1, Elsevier, Amsterdam, 2006.

[WEL 08] WELCH I., GOYAL A., "A comprehensive look at the empirical performance of equity premium prediction", *The Review of Financial Studies*, vol. 21, no. 4, pp. 1455–1508, 2008.

[ZHU 13] ZHU X., ZHU J., "Predicting stock returns: a regime-switching combination approach and economic links", *Journal of Banking & Finance*, vol. 37, no. 11, pp. 4120–4133, 2013.

6

Style Factor Timing

Average excess returns from most common style factors have been declining gradually since 2008. On the other hand, correlations among factors and across regions are rising; factor performance is becoming increasingly nonlinear with periodic structural breaks. In this challenging environment, style rotation or factor timing provides another avenue for improving performance. Style timing does have its own pitfalls, e.g. the difficulties associated with any market timing strategy, low breadth of investment and heightened portfolio turnover. In this chapter, we show how macroeconomics, market sentiment, capital markets and seasonal variables can be used to predict future factor returns and risks.

6.1. Introduction

In academia style timing, along with market timing, has always been a controversial topic. There were a few rather dated papers on style rotation prior to 2008 (e.g. [BER 95, SOR 95, KAO 99, LEV 99] and [ASN 00]). Similarly, in the practitioners' world, factor selection was mostly based on the manager's discretion and factor weighting was primarily static in the same pre-2008 period.

The 2007 quant crisis and the subsequent 2008 global financial crisis have triggered a round of strong interest in factor timing or style rotation in academic research. For example, Limthanakom and Collver [LIM 10] document style momentum and find macroeconomic variables have a predictive power over future style returns. Ardia *et al*. [ARD 16] argue for the economic benefits of timing style factors. There remains considerable suspicion towards the possibility of style timing. For example, Corbett [COR 16] finds that US equity mutual fund managers who frequently change styles (market, size, value and momentum) underperform their peers. Asness *et al*. [ASN 17] suggest that contrarian value timing of factors is not very effective.

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As we elaborate with great detail in [LUO 17a, LUO 17b], there is strong evidence suggesting that:

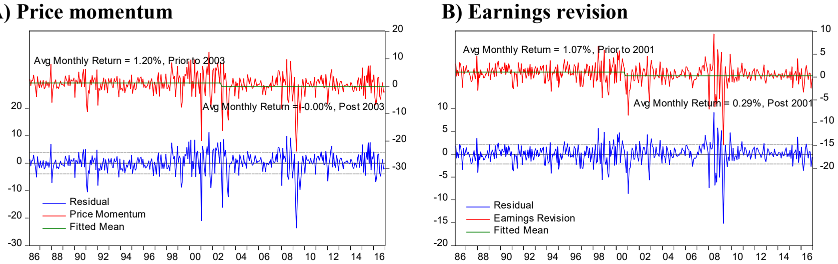
– factor returns are time varying;

– the average return across factors has been declining;

– factor returns have periodic structural breaks and large outliers.

Figures 6.1(a) and (b) show the breakpoint regression (see [BAI 98]) on the time series return[1] of value (earnings yield) and price momentum (12M-1M total return) in the United States. Bai and Perron's technique [BAI 98] is a common statistical technique used to identify potential structural breaks in time series data. It is evident that both value and momentum return time series have at least one breakpoint, as shown in the upper portion of the graphs in the early 2000s. The average monthly returns of both factors were around 1% in the 1980s/1990s but plunged sharply in recent years.

A) Price momentum **B) Earnings revision**



Sources: Bloomberg Finance LLP, FTSE Russell, S&P Capital IQ, Thomson Reuters, Wolfe Research Luo's QES.

Figure 6.1. *The structural changes in factor performance. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

Beyond the two well-known quant crises in the summer of 2007 and March–May 2009, the performance, as shown as shown in Figure 6.2, of six common style factors[2], in four major regions of the world (US, Europe, Japan and Asia ex Japan [AxJ]) reveals a few interesting patterns:

1 For the purpose of this chapter, factor performance is measured using long/short quintile portfolios, where we long the best ranked stocks (equally weighted) and short the worst ranked stocks (also equally weighted). The portfolios are constructed on a country/sector neutral basis. Portfolios are rebalanced monthly without taking into account transaction costs and short availability. We use local currency to compute factors and stock returns.

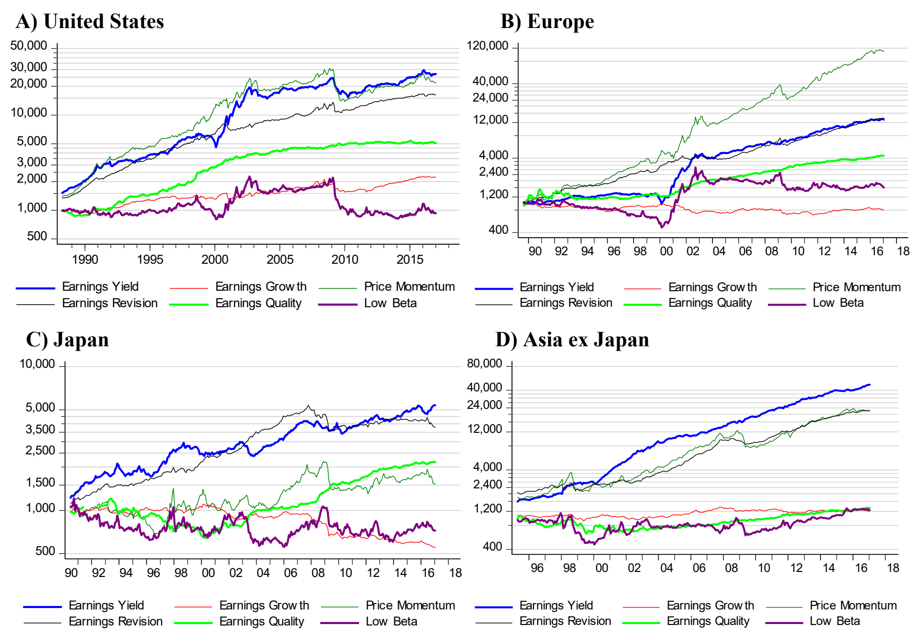
2 The six style factors are trailing earnings yield, year-over-year EPS growth, price momentum (trailing 12-month return excluding the most recent month), Three-month EPS Revision, Earnings Quality (based on Sloan [SLO 96] accruals concept), and Low Beta. For the purpose of this chapter, we divide the world into nine regions (the United States, Canada, Europe, UK, Asia ex Japan, Japan, Australia and New Zealand, LATAM and emerging EMEA. We include both large- and small-cap stocks in our investment universe.

– factor performance was much stronger in the early years prior to 2007. Post 2008, in the United States and Japan in particular, returns compressed while risk exacerbated considerably;

– most factors deliver positive returns in the long term but are subject to periodic drawdowns. The downside risk can be substantial, especially for price momentum and low beta strategies. The low-risk factor is the most volatile factor in almost all regions;

– factor performance tends to be far stronger in Europe and AxJ than in the United States and Japan;

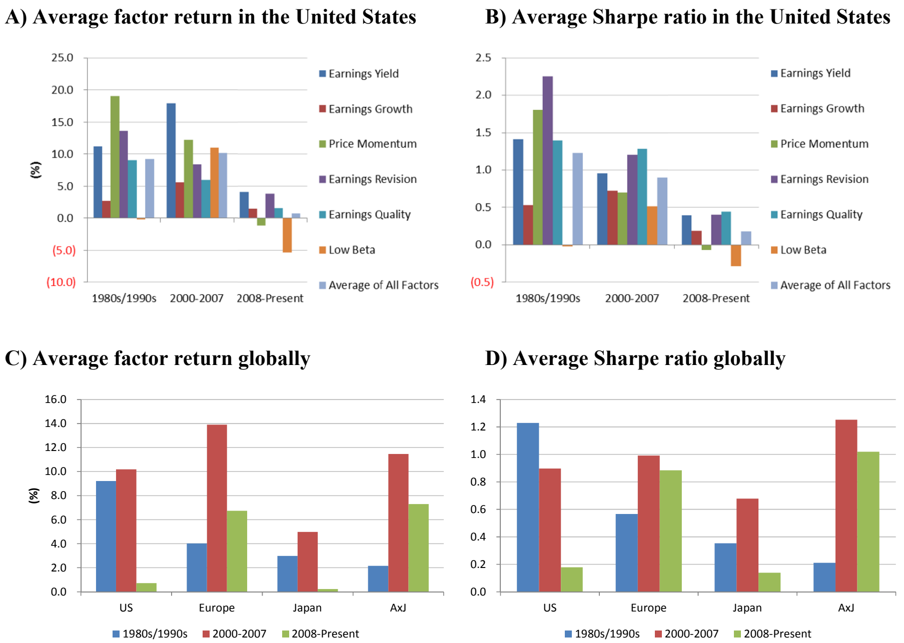
– in the United States, value has the highest cumulative return, while accounting quality has the best risk-adjusted performance. In Europe, the price momentum factor dominates in terms of returns, while accounting quality has the highest Sharpe ratio. In Japan, price momentum, earnings growth and low beta anomalies virtually do not exist, while value and earnings revision have reasonable performance. In AxJ, the classic value, price momentum and earnings revision have all produced decent performance.



Sources: Bloomberg Finance LLP, FTSE Russell, S&P Capital IQ, Thomson Reuters, Wolfe Research Luo's QES.

Figure 6.2. *The performance of common equity style factors. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

In the US equity market, the performance of most common factors (see Figures 6.3(a) and (b)) clearly shows significant decay in the post-2008 period. Globally, in all major regions, factor performance has declined in recent years, especially in the United States and Japan (see Figures 6.3(c) and (d)).



Sources: Bloomberg Finance LLP, FTSE Russell, S&P Capital IQ, Thomson Reuters, Wolfe Research Luo's QES.

Figure 6.3. *The challenges ahead of us. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

6.1.1. *The culprit and the verdict*

It has long been debated whether the decline of factor performance in recent years is transitory or permanent. We have always argued that the challenge is secular and the good old days are over, for a number of reasons:

– intensified competition and market efficiency are reflected in rising correlation among factors in the same region and among regions for the same factor, coupled with heighted downside risk;

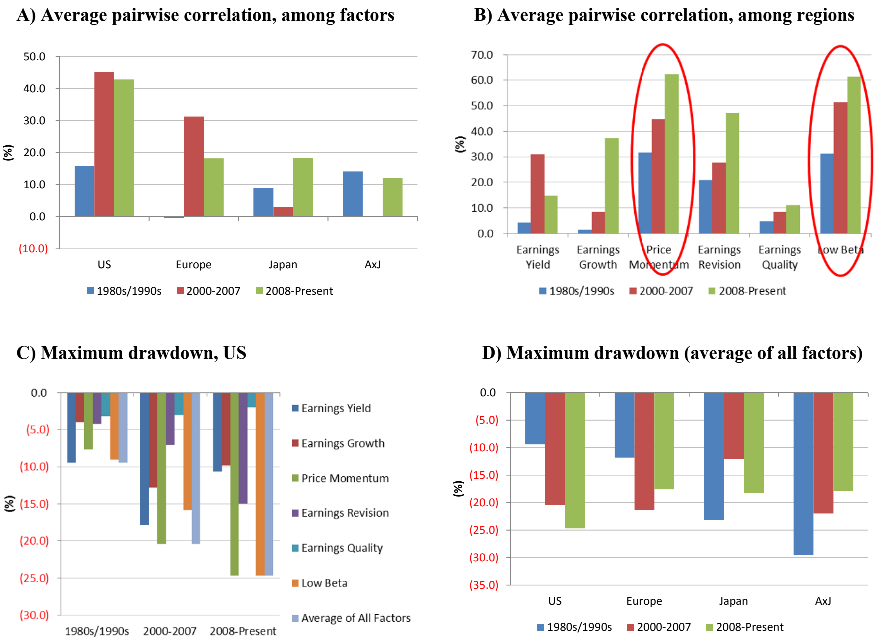
– geopolitical risk and uncertainty are playing an increasingly dominant role in investing. The investment world is marked by periodic risk-on and risk-off, which dictates the performance of investment styles (and factors);

– factor payoff patterns are becoming perceptibly nonlinear. The traditional Fama–French [FAM 93, FAM 96] type of linear factor models no longer captures the cross-sectional risk and return trade-offs very well;

– *ad hoc* and static factor allocations are likely to face the biggest headwind.

6.1.2. *Rising factor correlation and heightened downside risk*

As shown in Figure 6.4(a), the pairwise correlation among factors (in the same region) has either increased significantly (in Japan and AxJ) or remains high (in the United States and Europe) in recent years. Furthermore, the correlation of the same factors across regions has spiked even higher (see Figure 6.4(b)). The surge of cross-regional correlation for the price momentum and low-risk factors is particularly noticeable. The spillover of financial and political risk across regions is at a speed that we have never seen before. The conventional wisdom of diversifying across factors and regions is being heavily scrutinized.



Sources: Bloomberg Finance LLP, FTSE Russell, S&P Capital IQ, Thomson Reuters, Wolfe Research Luo's QES.

Figure 6.4. *Rising factor correlation and heightened downside risk. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

However, much of the struggle, especially for the US market, is due to the risk rally in March–May 2009. In less than 3 months from March 9 2009 to June 1 2009, the price momentum and low beta strategies went down almost –50%[3]. As shown in Figures 6.4(c) and (d), the downside risk of most factors in the United States has extended in recent years and remains high in Europe and Japan.

6.1.3. *The impact of risk-on/risk-off*

The post-2008 period has been marked by a periodic shift of investor's risk sentiment. A common phrase used in the investment industry is risk-on/risk-off[4]. There is not a unanimous definition but, generally speaking, risk-on refers to an environment in which investors are optimistic about the future and therefore are willing to invest in risky assets. On the other hand, in a risk-off regime, investors worry about the underlying investment environment and stay away from risky stocks.

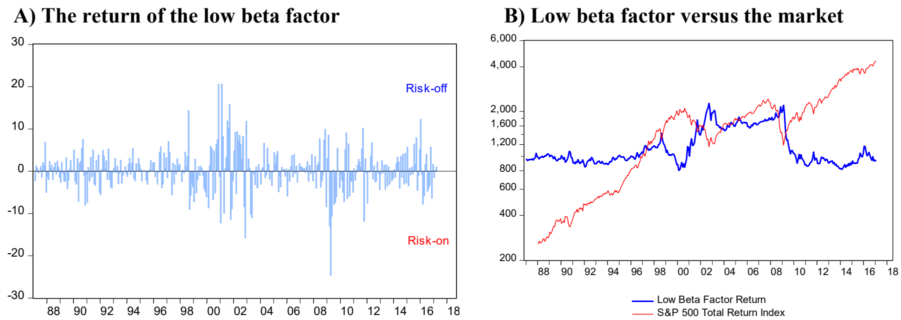
A simple way to understand risk-on/risk-off is to examine the return of the low beta factor. By construction, the low beta factor invests in the top 20% of stocks with the lowest beta and simultaneously shorts the bottom 20% of stocks with the highest risk. When the return of the low beta portfolio is positive, it indicates a risk-off regime (i.e., investors pile into low risk stocks), and vice versa for positive return periods as risk-on.

Figure 6.5(a) shows the monthly return of the low beta portfolio in the US market. It is evident that our simple risk-on/risk-off indicator captures the major market turning points – consistent positive returns (risk-off) during early 2000 (the burst of the tech bubble) and 2008 (financial crisis) and, similarly, consistent negative returns (risk-on) in late 1999 (tech bubble) and in the March–May 2009 risk rally. Although the low beta factor is negatively correlated[5] with the market (see Figure 6.5(b)), they are different. The market and the low beta factor can rally (or dip) at the same time.

3 Price momentum essentially invests in stocks with highest past 12-month returns (and shorts the ones with the lowest returns). At the bottom of the market on March 9 2009, stocks with the best performance tended to be mostly low beta stocks (in a bear market environment). Therefore, price momentum and low beta was essentially the same factor at the time. Indeed, the correlation between the two factors from March 9 2009 to June 1 2009 was around 99%.

4 The phrase "risk-on and risk-off" has become a cliché in recent years. For lack of a better name, we shall continue to use it in this chapter.

5 The correlation is about –69%.



Sources: Bloomberg Finance LLP, FTSE Russell, S&P Capital IQ, Thomson Reuters, Wolfe Research Luo's QES.

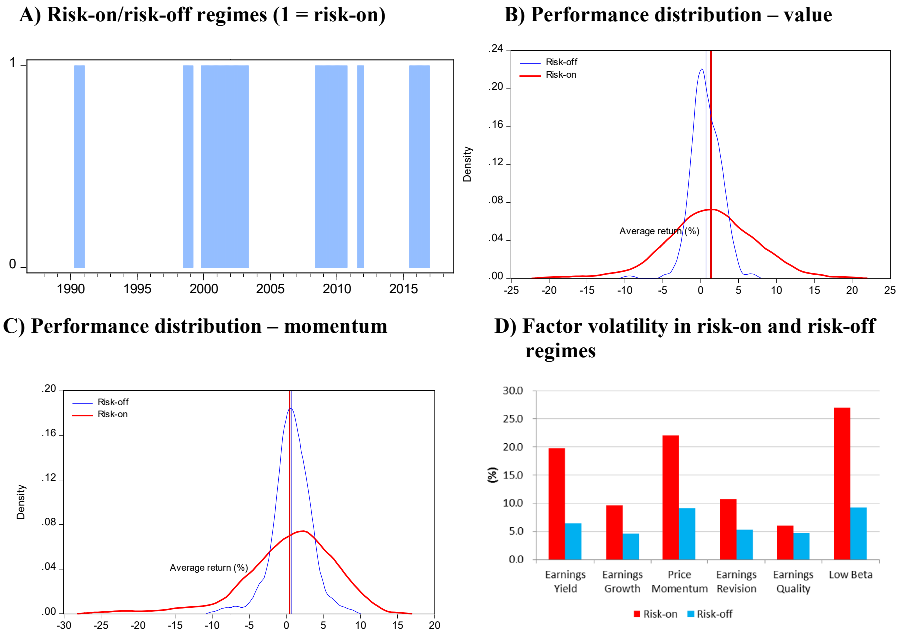
Figure 6.5. *A simple risk-on/risk-off indicator. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

One problem of using our risk-on/risk-off factor directly is that the indicator is a little too noisy. To extract the true signal from noise, we apply a Markov regime switching (MRS) model and use the smoothed[6] probability as our improved risk-on/risk-off regime classification. As shown in Figure 6.6(a), the smoothed risk-on/risk-off regime is currently much more stable. Indeed, the estimated probability of remaining in a risk-on (risk-off) regime is 94% (97%). The average duration of risk-on (risk-off) regimes is about 18 (38) months. The average return of the low beta factor is significantly lower in the risk-on regime (–3.1% per year) than in the risk-off environment (2.2%).

For most factors, the performance is weaker in a risk-on environment but, more importantly, the risk (i.e. dispersion in return distribution) and in particular the downside risk tends to be materially higher in risk-on regimes. As shown in Figures 6.6(b) and (c), the return distribution for both value and momentum factors is much flatter in risk-on regimes, with a considerably longer left tail (i.e. negative return). The frequent risk-on/risk-off switches in the post-2008 period are the main reason behind the turbulent performance for many quant funds. Lastly, as shown in Figure

6 Technically speaking, there are three regime probabilities: one-step-ahead forecast, filtered and smoothed. The smoothed probability is based on a Markov regime switching model using the entire data set; therefore, it provides the most precise estimate. However, the smoothed estimate is in-sample in nature and cannot be used in real-time forecasting. For our purpose, as we are trying to understand the impact of risk-on/risk-off rather than making real-time predictions, it is better to use the smoothed probability. On the other hand, the true out-of-sample, one-step-ahead and filtered probabilities are all dynamically updated. The filtered probability is based on the model using information available at the time of forecast (still in-sample), but is generally more conservative than the smoothed one. The one-step-ahead probability is estimated using data at one period before the prediction time. Therefore, the prediction is out-of-sample.

6.6(d), volatility tends to be multiple levels higher in risk-on regimes for almost all common factors.

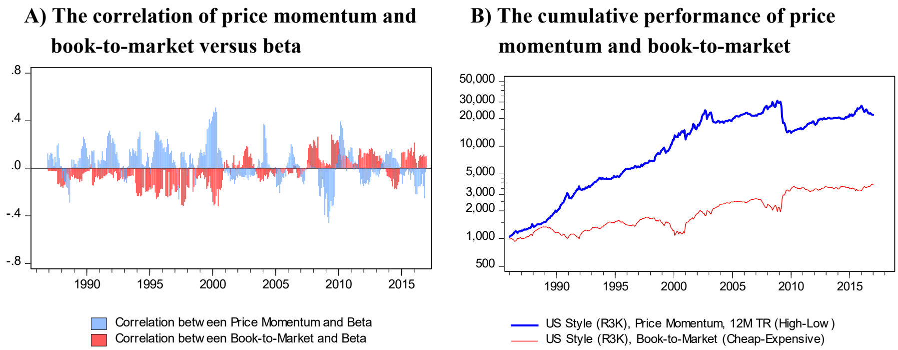


Sources: Bloomberg Finance LLP, FTSE Russell, S&P Capital IQ, Thomson Reuters, Wolfe Research Luo's QES.

Figure 6.6. *Risk-on and risk-off in the US equity market. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

In a risk-on/risk-off world, many factors are simply proxies for risk (either risk seeking or risk averse). For example, 2016 was an interesting year because the performance of quant funds was very binary – either very strong or very poor. It all depends on whether they were on the right or wrong side of the risk regime switches.

Two factors dominated the performance of most multifactor models in 2016 value (proxied by book-to-market) and momentum (e.g. 12M return excluding the most recent month). As shown in Figure 6.7(a), book-to-market was positively correlated to beta in the sense that value stocks were cyclical and benefited from an improvement in investors' risk appetite. On the other hand, price momentum was negatively exposed to beta – winners' stocks were mostly low risk, which underperformed considerably since February 2016. The performance of book-to-market and price momentum forms a perfect mirror image (see Figure 6.7(b)). Managers thought they invested in multifactor models but, in the end, most portfolios resembled unidimensional market timing in 2016.



Sources: Bloomberg Finance LLP, FTSE Russell, S&P Capital IQ, Thomson Reuters, Wolfe Research Luo's QES.

Figure 6.7. *Cross-sectional correlation with risk. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

6.1.4. *Factor payoff patterns are becoming increasingly nonlinear*

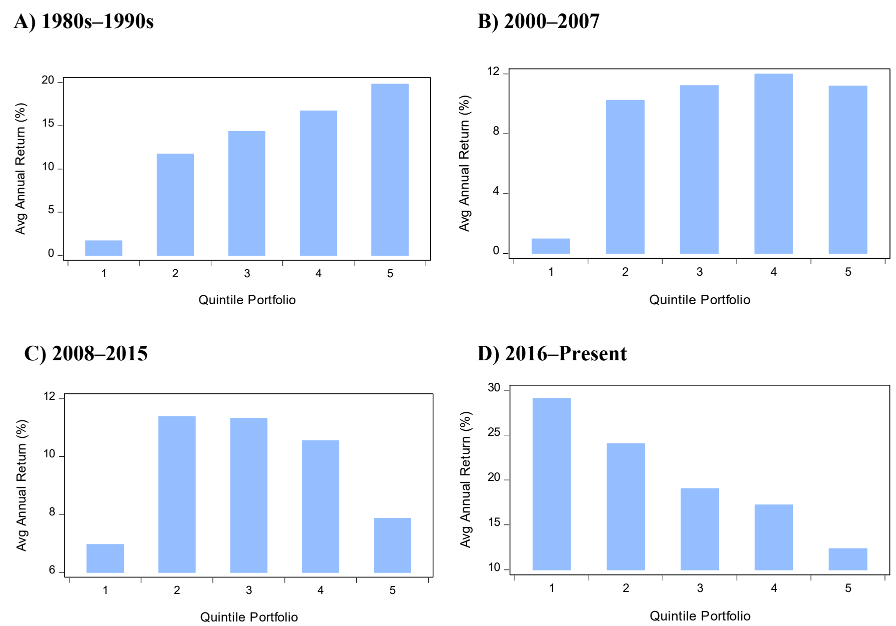
Many of the traditional market anomalies or stock selection factors were discovered and the underlying academic papers published before 2007. At the time, the relationship between factors and forward stock returns was primarily linear or at least monotonic. Not surprisingly, the predominant modeling techniques were also linear in nature, e.g. OLS regression and mean-variance optimization.

As the market evolves, possibly due to a combination of arbitrage by investors and changes in the underlying market regimes, the payoff patterns are becoming progressively nonlinear.

Figures 6.8(a)–(d) show the payoff patterns for one of the cornerstones of quantitative investing, price momentum, over four periods. We form five quintile portfolios based on the month end price momentum factor. Then, we rebalance the portfolio monthly. The four graphs illustrate the average returns of the five momentum quintile portfolios over time. If the payoff pattern of the price momentum factor conforms to the Jegadeesh and Titman [JEG 93] study, we should expect a linear monotonic upward trend. In the early years, in the 1980s–1990s (see Figure 6.8(a)), that was exactly what we would expect, albeit the Quintile 1 portfolio had a disproportionally low return, possibly due to arbitrage limits[7]. In the golden years of 2000–2007 the pattern became much less linear but low momentum stocks in Quintile 1 still massively underperformed; therefore, investors who had shorted poor momentum stocks would have generated outsized returns. In the third period, from 2008 to 2015, the pattern resembled an inverted U-shape, where both poor

7 Shorting was more difficult and costly in the 1980s–1990s.

momentum stocks in Quintile 1 and the best momentum firms in Quintile 5 underperformed the middle three quintile portfolios. In 2016, the pattern completely reversed to a monotonic downward trend.



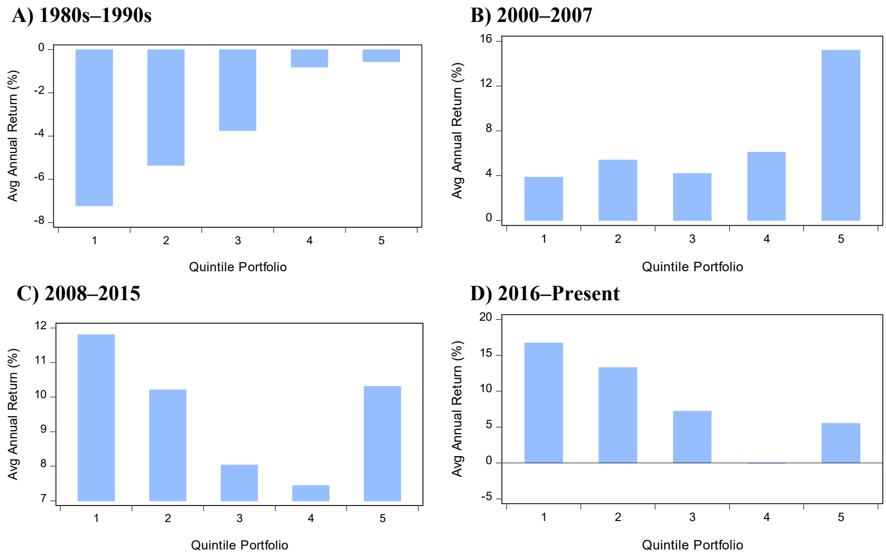
Sources: Bloomberg Finance LLP, FTSE Russell, S&P Capital IQ, Thomson Reuters, Wolfe Research Luo's QES.

Figure 6.8. *Price momentum factor in the United States*

Outside of the US equity market, trends are generally not as severe as in the United States. However, we also notice the patterns for many factors in many regions have changes, e.g. the earnings revision factor in Japan (see Figure 6.9).

Extending our modeling techniques beyond linear regression poses a series of challenges to managers. It is not due to lack of nonlinear algorithms – in fact, there are far too many nonlinear models to choose from. Mainstream finance research is still predominantly linear in nature. Nonlinear models are often labeled as and confused with data mining. Even those limited research papers that reveal nonlinear patterns are *ad hoc* in many ways.

Therefore, factor returns are no longer stationary, subject to periodic structural breaks and sensitive to risk-on and risk-off regimes. On the positive side, this does provide opportunities for factor timing. Style rotation has always been a controversial topic within the investing community. The opponents argue that the breadth of style rotation is limited (as we have far fewer factors than stocks), timing is difficult (if not impossible), time series data history is short and factor timing increases portfolio turnover. However, since the performance of style rotation models tends to be uncorrelated to the excess return from style factors, even a modest skill can still provide great diversification benefit.



Sources: Bloomberg Finance LLP, FTSE Russell, S&P Capital IQ, Thomson Reuters, Wolfe Research Luo's QES.

Figure 6.9. *Earnings revision factor in Japan*

6.2. Why does it matter?

To measure the upside from factor timing, we can provide a simple simulation. We start from eight common equity factors: trailing earnings yield (we prefer companies with high earnings yield), book-to-market (we buy companies with high book-to-market), consensus FY1/FY0 EPS growth (we prefer companies with high earnings growth), price momentum as defined by 12M total return excluding the most recent month, analyst sentiment measured by 3M EPS revision (we buy companies with positive earnings revisions), profitability (return on equity (ROE) – we like firms with high ROEs), leverage (debt/equity ratio – we prefer companies with low financial leverage) and earnings quality (Sloan's accruals – we buy companies with low accruals).

To demonstrate the potential upside from style rotation, we create a perfect foresight model, assuming that we have 100% accuracy in predicting the next month's factor return. Essentially, at each month end, we conduct Grinold and Kahn's[8] optimization (essentially a mean-variance optimization of the factor space):

$$argmax_{\omega} IR = \frac{\omega' \widetilde{IC}}{\sqrt{\omega' \Sigma_{IC} \omega}},$$

where:

– ω is a $(K \times 1)$ vector of factor weights;

– $\widetilde{IC}$ is a $(K \times 1)$ vector of the expected factor information coefficient (IC)[9];

– Σ_{IC} is a $(K \times K)$ covariance matrix of factor IC.

The above optimization problem has a closed-form solution, if we do not have any constraints[10]:

$$\widehat{\omega} = \Sigma_{IC}^{-1} \widetilde{IC}$$

where $\widehat{\omega}$ can be further normalized as $\widetilde{\omega} = \frac{\widehat{\omega}}{i' \cdot \widehat{\omega}}$ and i is a $(K \times 1)$ vector of 1's; then the weights add up to one.

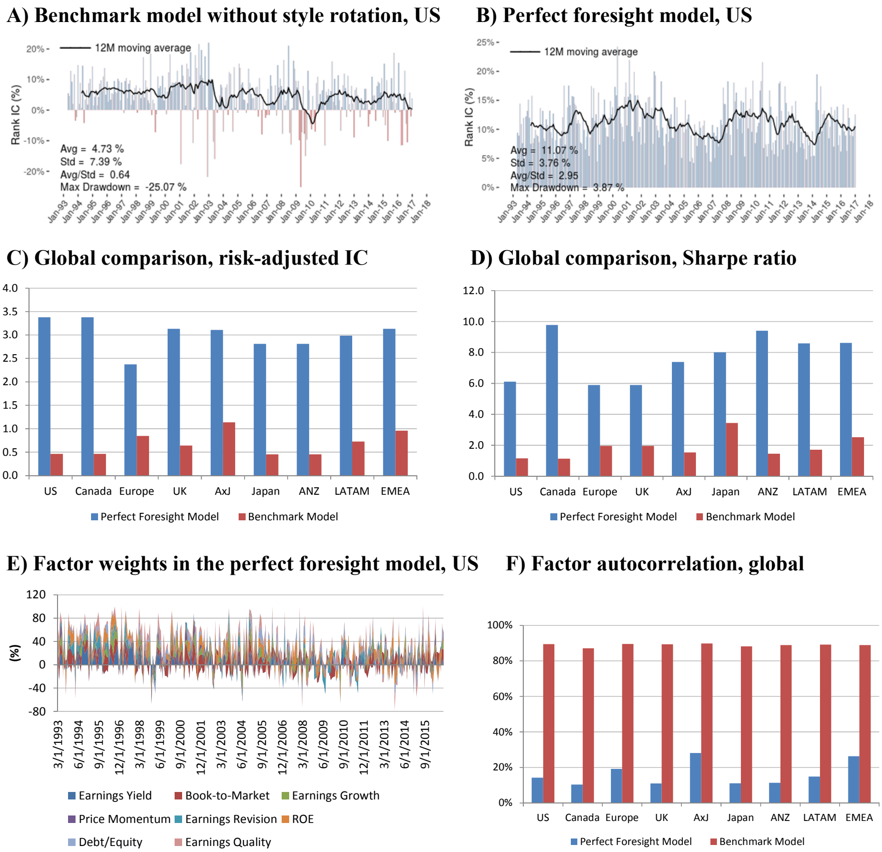
There are two input parameters for Grinold and Kahn's optimization – the vector of expected factor IC ($\widetilde{IC}$) and the covariance matrix (Σ_{IC}).

For the perfect foresight model, we set the vector of predicted factor IC ($\widetilde{IC}$) as the actual next month's factor IC. This essentially assumes that we are 100% correct in predicting future factor performance. The risk model, i.e. the factor covariance matrix, is estimated using a 10-year rolling window sample covariance matrix. Therefore, we assume that we have perfect skill in predicting factor return but no special skill in forecasting risk.

For this optimization, we do not add any minimum weight constraint. Therefore, we can use the closed-form formula $\widehat{\omega_t} = \Sigma_{IC}^{-1} IC_{t+1}$ to derive factor weights. Lastly, we use this perfect foresight model as our stock-selection model and track the model performance over time.

8 See [GRI 99].
9 IC or information coefficient is commonly used to measure factor performance. IC is essentially the correlation between the current period's factor exposures and the next period's stock returns, computed cross-sectionally. If a factor has perfect prediction of future stock returns, the correlation (or IC) should be 100%. If a factor is completely random, the IC would be close to 0%.
10 Details can be found on page 203, Equation 7.17 in [QIA 07].

To measure the performance of a benchmark model (BM)[11] and our perfect foresight model, in Figure 6.10(a) we show the monthly IC (correlation between our model forecasts and the following month's stock returns). The perfect foresight model's performance (as measured by risk-adjusted IC[12]) is almost eight times higher (see Figure 6.10(b)). If we could predict factor performance with 100% precision, our stock selection model would not have had a single down month in the past 23 years.



Sources: Bloomberg Finance LLP, FTSE Russell, S&P Capital IQ, Thomson Reuters, Wolfe Research Luo's QES.

Figure 6.10. *The upside potential from style rotation. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

11 The benchmark model (BM) equally weighs the eight factors. Details can be found in [LUO 17b].

12 Risk-adjusted IC is computed as the ratio of average IC and the standard deviation of IC, as a proxy of Sharpe ratio.

Globally, we observe the same impact. The perfect foresight model boosts the risk-adjusted IC by 300–700% (see Figure 6.10(c)) and Sharpe ratio by 300–900% (see Figure 6.10(d)) in the nine regions.

Factor weights in the perfect foresight model change dramatically from month to month, with very high turnover (see Figure 6.10(e)). The average signal autocorrelation[13] drops by over 80% from the BM (see Figure 6.10(f)). This once again highlights the point that, if we do have great predictive power, the portfolio is most likely to have high turnover. Therefore, high turnover itself is neither a friend nor foe. It critically depends on our skill, transaction costs, the size of the portfolio and a few other parameters.

6.3. Modeling techniques

Broadly speaking, there are two modeling techniques for style rotation – cross-sectional and time series. The most powerful approach to model style factor returns are generally different from the ones used for stock selection. We have a far smaller number of factors than stocks. A cross-sectional ranking is likely to be difficult. Therefore, time series regression techniques are likely to be more effective.

For demonstration purposes, in this section we choose 15 common style factors to show how style rotation can be applied in practice: trailing earnings yield, dividend yield, book-to-market, EBITDA/EV, expected 5Y EPS growth, expected FY1/FY0 EPS growth, price momentum (12M-1M), price reversal (1M), earnings revision (FY1 EPS, 3M), ROE, debt/equity ratio, earnings quality (Sloan's accruals), beta, Amihud illiquidity and size (log market capitalization).

For each of the above 15 factors, we construct a long/short quintile portfolio, neutralized for country and sector effect. Stocks are equally weighted in both long and short sides. We track the 15 factor portfolios for each of the nine regions (the United States, Canada, Europe, UK, AxJ, Japan, Australia and New Zealand (ANZ), LATAM and EMEA).

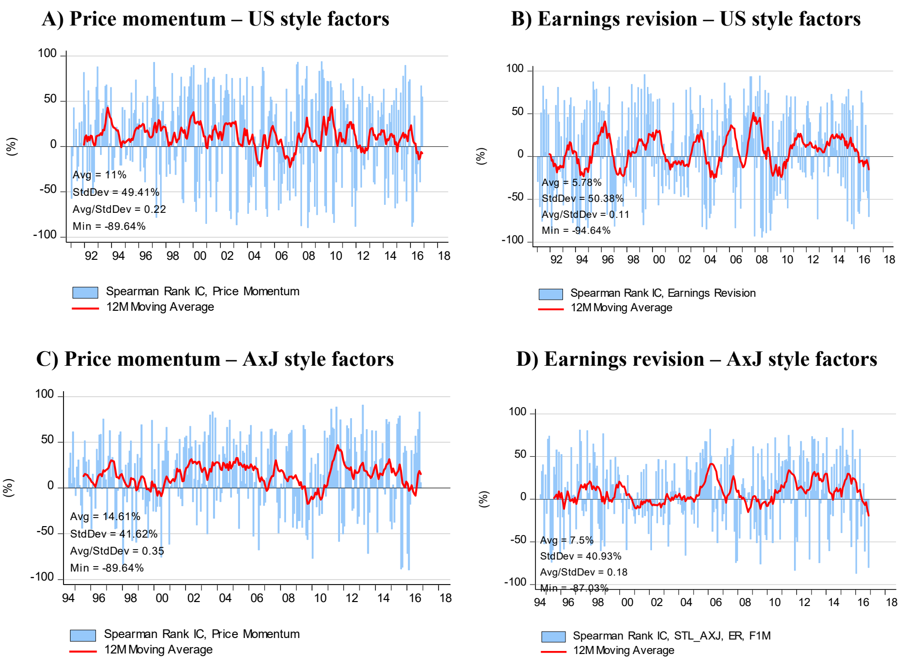
6.3.1. *Cross-sectional approach*

Using the cross-sectional approach, the global macromodeling process mirrors the bottom-up stock selection. We perform our analysis cross-sectionally for all 15 style factors at the same point in time. The predictors used in cross-sectional analysis are typically asset specific, e.g. the valuation and price momentum of each

13 Signal autocorrelation is the correlation between the model prediction in the previous month and current month. If a model is static, the autocorrelation is 100%. For such a model, the portfolio turnover is 0% but the model also has no predictive power.

style factor. For example, Zaremba and Szyzka [ZAR 16] document significant factor momentum in emerging markets, using the Polish equity market as an example. Arnott *et al*. [ARN 16, ARN 17] and Asness *et al*. [ASN XX, ASN 17] emphasize primarily how valuation can be used in factor timing and find conflicting results.

To measure the effectiveness of cross-sectional variables in predicting future style factor returns, we compute factor timing IC. For example, Figures 6.11(a)–(d) show the performance of price momentum and earning revisions in equity factor rotation from a cross-sectional context. The price momentum signal for factors is defined as the cumulative return of each style portfolio over the past 12 months, similar to how price momentum is defined at the stock level. Similarly, earnings revision is defined by the difference of median earnings revision at the long quintile and short quintile portfolios. At each month end, we compute the price momentum (and earnings revision) for each style factor portfolio. Then, IC is defined as the correlation between the current month's price momentum with the next month's style factor portfolio return.



Sources: Bloomberg Finance LLP, FTSE Russell, S&P Capital IQ, Thomson Reuters, Wolfe Research Luo's QES.

Figure 6.11. *The predictive power of momentum and earnings revision in style rotation. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

Both factors appear to have reasonable predictive power over next month's style portfolio returns, in both the United States and AxJ. However, we need to keep in mind that the breadth of our investment universe is rather limited – we only have 15 style portfolios.

6.3.2. *Time series approach*

The time series approach models each asset classes (e.g. style factors) individually. The predictors used in time series models can be applied to most asset classes, e.g. GDP growth, inflation, yield spread and other economic and capital market variables. We form our return forecast for each asset class independently[14]. Then, we compare the return predictions of each asset class jointly to build our portfolio. Using a simple regression model as an example, the typical time series model can be specified as:

$$f_{i,t} = \alpha_{i,t} + \sum_{k=1}^{K} \beta_{i,k,t} E_{k,t-1} + \varepsilon_{i,t}$$

where:

– $f_{i,t}$ is the return of style portfolio i at time t;

– $\alpha_{i,t}$ and $\beta_{i,k,t}$ are the coefficients to be estimated by the regression, for factor portfolio i at time t;

– $E_{k,t-1}$ is the kth macro variable at time $t-1$;

– K is the number of predictors;

– $\varepsilon_{i,t}$ is the regression residual of asset i at time t.

For example, we may expect that the return from a value factor (e.g. the return of the earnings yield factor) can be possibly explained by economy cycle (proxied by the lagged value of industrial production (MoM percentage change)). When we estimate the model for momentum factor return, we still use the same predictor – the MoM change in industrial production. The intercept ($\alpha_{i,t}$) and slope ($\beta_{i,k,t}$) are different for value versus momentum factors.

14 Time series analysis offers a large selection of modeling techniques. We are certainly not limited to single equation models. All style portfolios can be modeled jointly, via SUR (Seemingly Uncorrelated Regression), VAR (Vector Autoregressive), VECM (Vector Error Correction Model), etc. Detailed discussion will be covered in a forthcoming research paper with Wolfe Research, "From nowcasting to forecasting".

The functional form does not have to be linear and the estimation technique is not limited to ordinary least squares. A general setup of the model is:

$$f_{i,t} = \varphi(\boldsymbol{\theta}_{i,t})\boldsymbol{E}_{t-1} + \varepsilon_{i,t}$$

where:

– $\varphi(.)$ is the functional form;

– $\boldsymbol{\theta}_{i,t}$ is a vector of model parameters to be estimated empirically for asset i at time t;

– $\boldsymbol{E}_{t-1}$ is the $(K \times 1)$ vector of macro variables at time $t-1$.

The time series model is estimated by each asset class, using either a rolling window or an expanding window. Once the model parameters are estimated, the prediction of return for the next period, i.e. $t+1$, is therefore:

$$\hat{f}_{i,t+1} = \hat{\alpha}_{i,t} + \sum_{k=1}^{K} \hat{\beta}_{i,k,t} E_{k,t}$$

where:

– $\hat{f}_{i,t+1}$ is the predicted return for asset i at time t;

– $\hat{\alpha}_{i,t}$ and $\hat{\beta}_{i,k,t}$ are the estimated model coefficients.

Similarly, a more general form of prediction is:

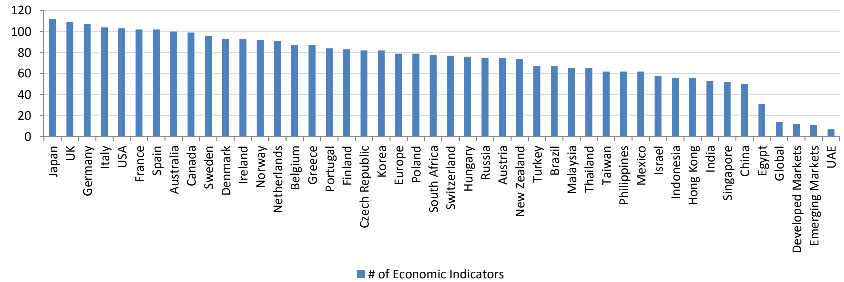
$$\hat{f}_{i,t+1} = \varphi(\hat{\boldsymbol{\theta}}_{i,t})\boldsymbol{E}_{t}$$

where $\hat{\boldsymbol{\theta}}_{i,t}$ is the vector of estimated model parameters.

6.4. Global macro database

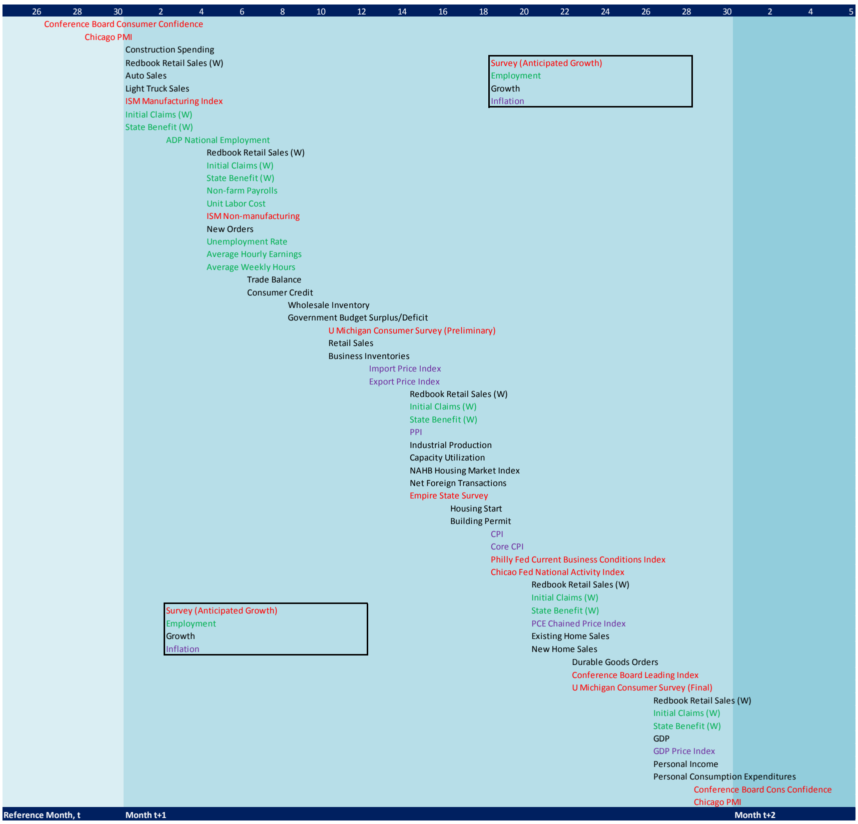
As we will show in this section, macroeconomic data have strong predictive power over future style factor return. However, few investors have the ability to systematically analyze economic data. There are a number of challenges in regards to economic data.

First of all, there is a dimensionality problem – there are simply too many global economic variables that we can potentially use. Figure 6.12 shows the ~3,500 major headline macroeconomic data series that we track for all countries and regions within the MSCI ACWI universe. We cannot possibly use all of them to time about a dozen common equity style factors.



Sources: Bloomberg Finance LLP, FTSE Russell, Haver, S&P Capital IQ, Thomson Reuters, Wolfe Research Luo's QES.

Figure 6.12. *Global economic indicators*



Sources: Bloomberg Finance LLP, FTSE Russell, Haver, S&P Capital IQ, Thomson Reuters, Wolfe Research Luo's QES.

Figure 6.13. *Stylized economic calendar in the United States. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

In addition to dimensionality, there are also a few other major hurdles when using economic data in real-time forecasting:

– frequency: economic data can be reported at a weekly, monthly, quarterly, annual or even irregular frequency; furthermore, the frequency for the same economic time series might change over time;

– reporting lag: economic data are often reported with a lag, ranging from a few days to multiple months;

– jagged edge problem: economic data are reported on different dates. For example, Figure 6.13 shows a stylized economic calendar in the United States. There could be multiple economic data series released on the same day but certainly not all economic variables are reported on the same day of the month.

6.4.1. *Policy uncertainty*

Political uncertainty dominated the world in 2016 with Britain's shocking exit from the European Union, the surprising result of the US election and the multiple geopolitical events occurring around the globe. The world in 2017 is set to surpass 2016, with multiple profound changes proposed by the new US administration, German and French elections, the potential trade conflicts regarding NAFTA, TPP, the United States/China, and the list goes on.

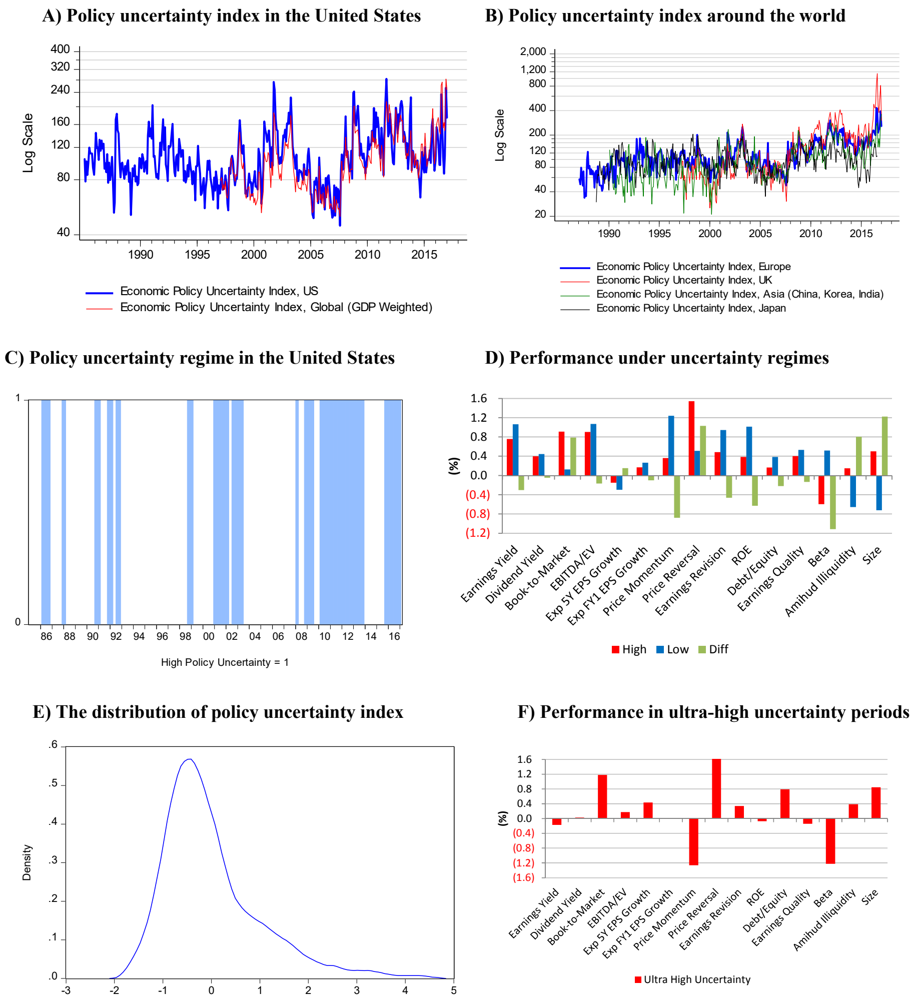
In a series of papers, three economics professors (see [BAK 15]) have constructed a suite of policy-related economic uncertainty indices for the major economies, e.g. the United States, Canada, Europe, UK, China and Japan. The policy uncertainty indices are mostly constructed using key word searches[15] from each country/region's leading newspapers. As shown in Figures 6.14(a) and (b), the policy uncertainty indices have reached all-time highs in almost all major countries. The policy uncertainty indices all have a positive serial correlation (i.e. high uncertainty tends to be followed by high risk in the near future). In the longer term, they show mean-reversal patterns[16].

For demonstration purpose, we can further fit an MRS model on to the US policy uncertainty index. Figure 6.14(c) shows the regime classification, where the highlighted areas indicate "high uncertainty". Each high uncertainty regime lasts for

15 For example, the key words can be "uncertain", "uncertainty", "economic", "economy" and other policy-relevant terms. For the United States, the authors also incorporate a number of tax code provisions scheduled to expire over the next 10 years and the estimated dispersions from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters.

16 An augmented Dickey–Fuller test strongly rejects the Null hypothesis of a unitroot process.

about 11 months on average (while low uncertainty regimes are about 18 months). It is evident that risk-on/risk-off regime switching occurs more frequently around and after recessions and major geopolitical events.



Sources: www.policyuncertainty.com, Bloomberg Finance LLP, FTSE Russell, S&P Capital IQ, Thomson Reuters, Wolfe Research Luo's QES.

Figure 6.14. *Political uncertainty and factor performance. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

The returns of our 15 style portfolios are significantly different in high versus low uncertainty regimes. Initially, it might be surprising to note that the defensive styles (e.g. dividend yield, low beta and price momentum) actually perform substantially worse, while cyclical factors (e.g. small cap, book-to-market) generate superior returns in a high uncertainty environment (see Figure 6.14(d)). Investors are probably either aware of the mean reversal nature of policy uncertainty or overly complacent at turning points. When uncertainty reaches an extremely high level, managers expect risk to come down and embrace risk-on styles.

The distribution of the policy uncertainty index is highly skewed to the right, meaning that we are more likely to see extremely high uncertainty than that implied by a normal distribution (see Figure 6.14(e)). Lastly, as shown in Figure 6.14(f), in ultra-high uncertainty periods (defined as above the two standard deviation band), investors become even more contrarian and start to chase cyclical styles such as size (small cap) and book-to-market and penalize low beta and price momentum. Mean reversal or StatArb styles tends to perform well in a risk-on/risk-off environment.

6.4.2. *Nowcasting and economic cycle*

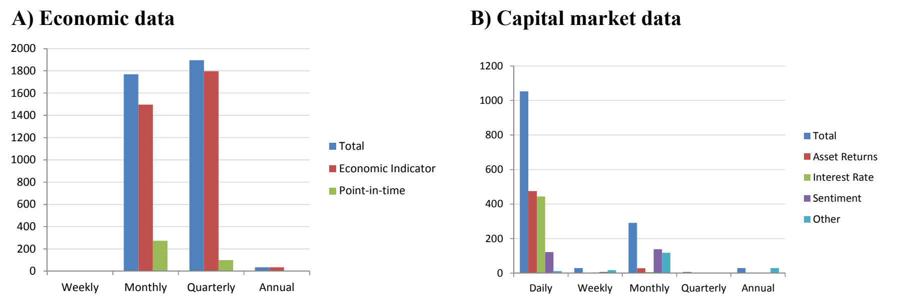
One of the most actively researched fields in macroeconomics in recent years is nowcasting. Nowcasting is a portmanteau of “now” and “forecasting”. It has been used for a long time in meteorology and recently ported into economics. It is about predicting the present, the recent past and the near future. The classic example is GDP.

US quarterly GDP typically comes in three flavors – advance (released toward the end of the month after the quarter end), revised (the second month after quarter end) and final (the third month after quarter end). Therefore, before we can even forecast the next quarter’s GDP, as at the quarter end, we only just have the data for the previous quarter’s GDP and do not even know the current quarter yet.

Beyond quarterly GDP, most economic data series are of monthly frequency. There are also weekly or even daily data, especially financial market data. As shown in Figure 6.15(a), monthly and quarterly frequencies account for the vast majority of economic variables, which is very different from capital market variables (mostly in daily frequencies, see Figure 6.15(b)). How to consistently model data series of different frequencies has been one of the biggest challenges in macroeconomic research.

The basic principle of nowcasting is to get a better and better estimate of the state of economy, as more and more information becomes available. Market participants monitor many economic data series, form expectations and revise the assessment whenever realizations diverge significantly from prior views.

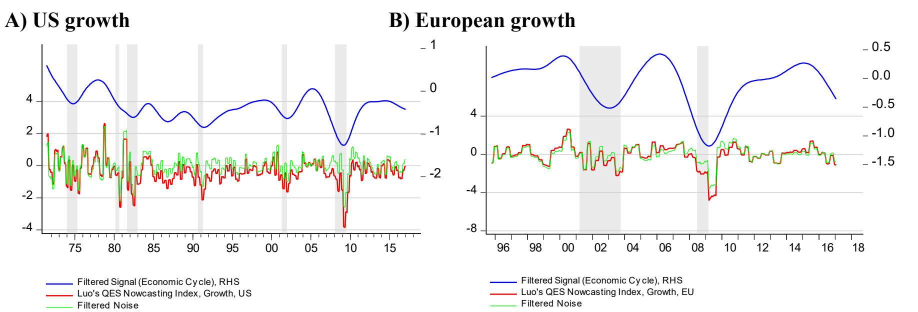
Here, let us show an example of our economic growth nowcasting index[17], which summarizes all key economic indicators released every day into one indicator.



Sources: Haver, Bloomberg Finance LLP, FTSE Russell, S&P Capital IQ, Thomson Reuters, Wolfe Research Luo's QES.

Figure 6.15. *Frequency of economic and capital market data. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

To extract the underlying signal (i.e. economic cycle) from noise, we apply the Hodrick–Prescott filter (see [HOD 97]). The Hodrick–Prescott filter is a statistical tool used in macroeconomics, especially in business cycle theory, to remove the temporary fluctuations from the long-term trend. Figures 6.16(a) and (b) show our nowcasting economic growth index for the United States and Europe[18], where the blue lines represent the long-term economic cycles.



Sources: Haver, Bloomberg Finance LLP, FTSE Russell, S&P Capital IQ, Thomson Reuters, Wolfe Research Luo's QES.

Figure 6.16. *Economic nowcasting index. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

17 We have four nowcasting indices (growth, anticipated growth, inflation and employment) for about 40 countries and regions.

18 The shaded areas indicate past recessions.

To understand the predictive ability of our nowcasting index, we can conduct two simple linear regressions:

$$f_{i,t} = \varphi_{i,0} + \varphi_{i,1}E_t + \epsilon_{i,t} \qquad [6.1]$$

and

$$f_{i,t+1} = \varphi_{i,0} + \varphi_{i,1}E_t + \epsilon_{i,t} \qquad [6.2]$$

where:

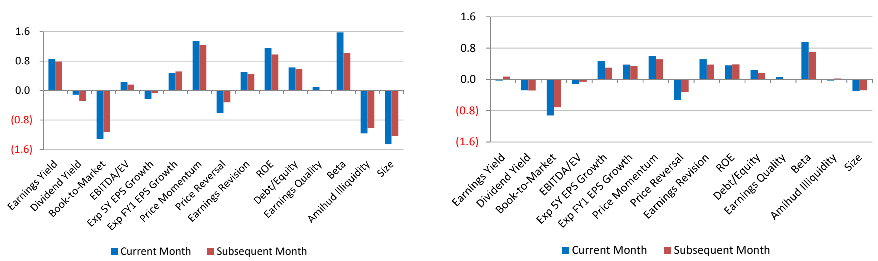
– $f_{i,t}$ is the return of style factor i at time t;

– E_t is our nowcasting economic growth index at time t.

The first regression [6.1] reveals the contemporaneous relationship between economic growth and factor performance, while the second equation [6.2] states whether the current economic situation can predict the next month's factor return.

As shown in Figure 6.17(a), our US nowcasting index is highly correlated to the current month's and equally predictive of next month's factor returns. Similar to what we observe for policy uncertainty, the relationship between economic growth and factor return is also contrarian in nature – when economic growth is strong, defensive factors (e.g. low beta, price momentum) tend to perform well, while book-to-market, dividend yield and price reversal styles are more likely to survive in economic downturns. The pattern is similar in Europe, albeit weaker (see Figure 6.17(b)). Lastly, we notice that the coefficients for the current month's and next month's factor returns are almost identical.

A) US **B) Europe**



Sources: Haver, Bloomberg Finance LLP, FTSE Russell, S&P Capital IQ, Thomson Reuters, Wolfe Research Luo's QES.

Figure 6.17. *The explanatory and predictive power of economic growth on factor performance. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

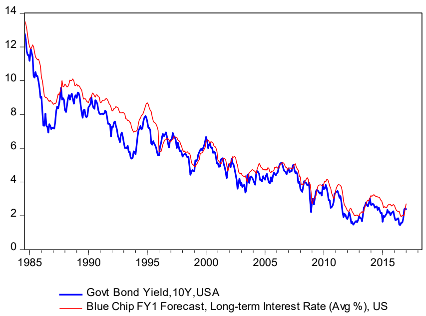
6.4.3. *Capital market variables*

With the Trump administration's proposed fiscal stimulus (infrastructure spending, tax cuts, etc.) at a time when the US economy is running at full employment, it is likely to trigger inflation and more hawkish Federal Reserve interest rate hikes. The consensus is that the US rates are likely to rise in the coming months (see Figure 6.18(a)). We cannot directly use the bond yield in our models because it shows a staggering downward trend over the past 30 years[19], but we can take a simple transformation by subtracting its own 12-month moving average:

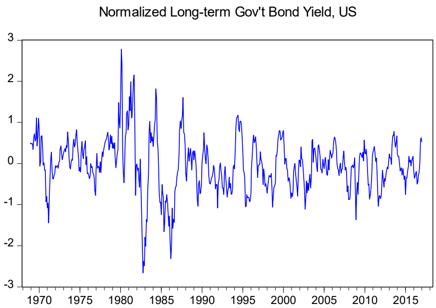
$$NormalizedYield_t = NominalYield_t - \frac{1}{12}\sum_{\tau=1}^{12} NorminalYield_{t-\tau+1}$$

The normalized yield shows far more attractive time series properties (see Figures 6.18(b) and (c) for the United States and Europe/UK/Japan, respectively).

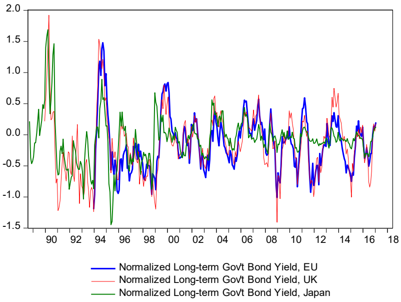
A) Current and expected bond yield, US



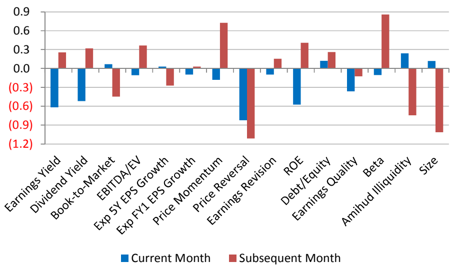
B) Normalized 10-year treasury bond yield, US



C) Normalized long-term gov't bond yield, global



D) Bond yield and factor returns



Sources: Haver, Bloomberg Finance LLP, FTSE Russell, S&P Capital IQ, Thomson Reuters, Wolfe Research Luo's QES.

Figure 6.18. *US 10-year treasury bond yield. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

19 In econometrics jargon, the US long-term interest rate is a trending time series.

We then carry out the same set of two regressions (using the current month's and next month's factor returns, respectively) against the normalized long-term bond yield. As shown in Figure 6.18(d), rising interest rates are detrimental to the concurrent performance of dividend yield, price reversal and ROE factors. However, the implication for forward factor returns can be quite different. In fact, if today's interest rate is high, we are better off by investing in price momentum and low beta styles for the future.

6.4.4. *Seasonality*

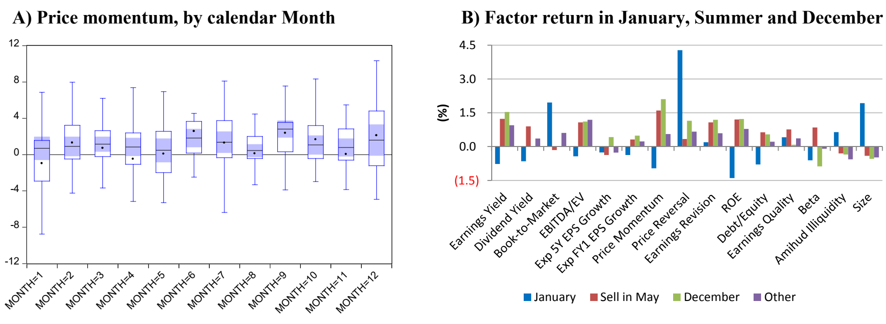
Seasonality in asset returns has long been documented. Three of the best known examples are:

– the *January effect* (see [ROZ 76]) states that small cap and high beta stocks outperform large cap and low beta stocks in January;

– *Sell in May and go away* (also known as the Halloween effect) suggests that the stock market tends to suffer from weaker returns in the months from May to September (see [BOU 02]);

– the *December tax loss selling and window dressing* anomaly argues that investors want to sell poorly performing stocks (e.g. low momentum) in December for tax reasons or have the incentive to hold high-quality/winning stocks for window dressing. Either argument suggests that momentum and quality styles should perform well in December.

Figure 6.19(a) shows the distribution of momentum factor return by calendar month. It is evident that momentum return is much higher in December and during the summer and much weaker in January. Examining the three seasons (i.e. January, May and December), the January effect appears to be strong for most factors, followed by the Sell in May effect (see Figure 6.19(b)).



Sources: Bloomberg Finance LLP, FTSE Russell, S&P Capital IQ, Thomson Reuters, Wolfe Research Luo's QES.

Figure 6.19. *The seasonality of factor returns. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

6.5. Conclusion

This chapter discusses the basics of style factor timing. Given the declining factor returns, rising factor correlations, changes in market regimes and increasingly nonlinear factor payoff patterns, style factor timing provides a new source of outperformance.

Despite the significant opportunities provided by factor timing, available academic research in this space is somewhat limited. Some of the most recent research papers (see [ARN 16, ARN 17] and [ASN XX, ASN 17]) primarily use factor valuation as a timing tool. Our research suggests that time series approaches using exogenous macrovariables can be more promising than traditional cross-sectional models. In particular we show the predictive power of macrouncertainty and, more importantly, nowcasting techniques in style rotation.

6.6. Bibliography

[ARD 16] ARDIA D., BOUDT K., WAUTERS M., “The economic benefits of market timing the style allocation of characteristic-based portfolios”, *North American Journal of Economics and Finance*, vol. 37, pp. 38–62, 2016.

[ARN 16] ARNOTT R., BECK N., KALESNIK V., “Timing Smart Beta Strategies? Of Course! Buy Low, Sell High!”, available at: https://www.research affiliates.com/en_us /publications/articles/541_timing_smart_beta_strategies_of_course_buy_low_sell_high.html, 2016.

[ARN 17] ARNOTT R., BECK N., KALESNIK V., “Forecasting Factor and Smart Beta Returns”, available at: https://www.researchaffiliates.com/en_us/publications/articles/595-forecasting- factor-and-smart-beta-returns.html, 2017.

[ASN 00] ASNESS C., FRIEDMAN J.A., KRIAL R.J. *et al.*, “Style timing: value versus growth”, *Journal of Portfolio Management*, vol. 26, pp. 50–60, 2000.

[ASN XX] ASNESS C., ILMANEN A., MALONEY T., “Practical market timing: sin a little”, *Journal of Investment Management*, forthcoming.

[ASN 17] ASNESS C.S., CHANDRA W., ILMANEN A. *et al.*, “Contrarian Factor Timing is Deceptively Difficult”, *Journal of Portfolio Management*, vol. 43, pp. 72–87, 2017.

[BAI 98] BAI J., PERRON P., “Estimating and testing linear models with multiple structural changes”, *Econometrica*, vol. 66, pp. 47–78, 1998.

[BAK 15] BAKER S.R., BLOOM N., DAVIS S.J., Measuring economic policy uncertainty, NBER Working Paper, available at: http://nber.org/papers/w21633, 2015.

[BER 95] BERNSTEIN R., *Style Investing: Unique Insight into Equity Management*, John Wiley & Sons, New York, 1995.

[COR 16] CORBETT A.J., Are style rotating funds successful at style timing? Evidence from the US equity mutual fund market, SSRN Working Paper, available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2736672, 2016.

[GRI 99] GRINOLD R., KAHN R., *Active Portfolio Management, A Quantitative Approach for Producing Superior Returns and Controlling Risk*, 2nd ed., McGraw-Hill, 1999.

[HOD 97] HODRICK R., PRESCOTT E.C., "Postwar US business cycles: an empirical investigation", *Journal of Money, Credit, and Banking*, vol. 29, no. 1, pp. 1–16, 1997.

[KAO 99] KAO D.L., SHUMAKER R.D., "Equity style timing", *Financial Analysts Journal*, vol. 55, pp. 37–48, 1999.

[LEV 99] LEVIS M., LIODAKIS M., "The profitability of style rotation strategies in the United Kingdom", *Journal of Portfolio Management*, vol. 26, no. 1, pp. 73–86, 1999.

[LIM 10] LIMTHANAKOM N., COLLVER C.D., Style momentum, SSRN Working Paper, available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1351006, 2010.

[LUO 17a] LUO Y., JUSSA J., WANG S., The Big and the Small Sides of Big Data, Wolfe Research, New York, 2017.

[LUO 17b] LUO Y., JUSSA J., WANG S., Signal Research and Multifactor Models, Wolfe Research, New York, 2017.

[LUO 17c] LUO Y., JUSSA J., WANG S., Style Rotation, Machine Learning, and The Quantum LEAP, Wolfe Research, New York, 2017.

[QIA 07] QIAN E.E., HUA R.H., SORENSEN E.H., *Quantitative Equity Portfolio Management: Modern Techniques and Applications*, 1st ed., Chapman & Hall, Boca Raton, 2007.

[SLO 96] SLOAN R.G., "Do stock prices fully reflect information in accruals and cash flows about future earnings", *Accounting Review*, vol. 71, no. 3, pp. 289–315, 1996.

[SOR 95] SORENSEN E.H., LAZZARA C.J., "Equity style management: the case of growth and value", in KLEIN R.A, LEDERMAN J. (eds.), *Equity Style Management: Evaluating and Selecting Investment Styles*, Irwin, Chicago, pp. 67–84, 1995.

[ZAR 15] ZAREMBA A., SZYSZKA A., Is there momentum in equity anomalies? Evidence from an emerging market, SSRN Working Paper, available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2778045, 2015.

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7

Go with the Flow or Hide from the Tide? Trading Flow as a Signal in Style Investing

We study the relationship between style-related trading and future style returns as well as risk for momentum, value and low volatility in the S&P 500 universe. To this end, we use a unique data set consisting of the entire daily equity flow executed through Bank of America Merrill Lynch for the period January 2014 to January 2017. This data set allows us to distinguish between trading by hedge funds, institutions and retail clients. We investigate style trading behavior and style returns as well as risk separately for different types of investors. The results show that style level imbalances are significantly related to future style returns and volatility. The nature and strength of the detected relationships are found to crucially depend on the investor type that generates the flow as well as the style considered. The economic significance of these findings is assessed using single and multifactor style timing strategies. We find that employing style level flow information can improve Sharpe ratios by as much as three times relative to simple volatility-managed benchmarks. The results have practical implications for investors as cross investor type style flow information may be used as an overlay indicator in constructing style portfolios.

7.1. Introduction

Investigating the information content in investor trading behavior and changes in holdings has been a widely addressed research question in empirical finance. Theoretically, order flow may be related to prices due to inventory [STO 78] or information-based effects [KYL 85]. The existence of the latter channel has led researchers to analyze whether holdings and changes in holdings of specific different investor groups are related to stock returns and/or risk in different ways. In

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this context, a significant body of the literature has focused on the trading behavior of institutional investors and in particular mutual funds [FRA 08]. Beyond that, linking investor trading behavior to asset prices has been extended to other types of institutional investors such as pension funds [LAK 92], hedge funds [AKB 15] and retail investors [KEL 10].

The by far largest part of this literature has focused on the analysis of the stock-level relationship between order flow and returns and risk in the time series or cross-section [BOE 06, CHO 04]. However, there is growing evidence [FRO 08] that especially institutional investors and hedge funds trade stocks based on common characteristics giving rise to *style investing*. Barberis and Shleifer [BAR 03] show theoretically that, if investors classify stocks into styles and trade them accordingly, returns of stocks within the same style comove more than those of stocks that do not share the same style characteristics. As such, styles become separate asset classes and naturally the question of how *style level flows* are related to *style level returns and risk* arises.

This chapter addresses this research question and provides an explorative analysis of the relationship between flows into three popular investment styles (momentum, value, and low volatility) and their risk-return profile. This is an important analysis for practitioners as trading flow information is a real-time indicator that, if found to be related to style returns and risk, can be used for style timing and multifactor portfolio decisions. Specifically, our approach is to first measure style trading behavior through flows into popular investment styles and then link these flows to style returns and risk. To measure style-related trading behavior, we employ a unique data set of actual client transactions through Bank of America Merrill Lynch's (BofAML, hereafter) equity division. BofAML is a major global equity flow execution house and as such one may expect trading flow information to be representative of the aggregate market. The data set employed in this chapter is unique as it does not only allow us to study aggregate style trading behavior but also style trading separately for different *types* of investors. This is important as the information content in style flows may vary by the investor type generating the flow. In fact, in a single stock flow setting, Boehmer and Wu [BOE 06] show that flows by different types of investors affect stock prices differently. The data set also has the advantage of being available on a daily basis making it much timelier than lower frequency holdings-based flow information typically employed in the existing literature. Specifically, we consider style investing activities by hedge funds, institutional, and retail investors and investigate if their trading behavior is informative for future momentum, value, and low volatility returns and risk.

We find that investor flows into momentum, value, and low volatility styles significantly predict future returns and volatility for long-only style portfolios over

1-month horizons. The predictive power of flows is found to be strongest for returns and varies by investor type and investment style. We generally find that net style inflows predict positive style returns with the exception of retail flows into momentum for which we find a negative relationship between net flows and future returns. In contrast to this, the predictive relationship between style inflows and future style volatility is mostly negative with style inflows predicting lower style volatility going forward. We then study the economic significance of these findings by devising simple single- and multifactor factor timing rules, which exploit the identified relationships between investor-level style flows and style performance. Our simple strategies add substantial economic value relative to simple volatility-managed style portfolio benchmarks. Moreover, signals across different investor type flows are found to be somewhat uncorrelated which allows combining them across different investor types. As an example, a value timing strategy constructed using a combination of hedge fund, institutional, and retail flow signals yields a Sharpe ratio of 1.35, three times as much as its volatility-managed and flow-agnostic counterpart. The improvement in Sharpe ratios is achieved through a combination of return improvement and volatility reduction utilizing both types of predictive information provided by style level flows. We finally extend our findings to a multifactor setting and find that using flow information can add value in this context as well. These findings are important for the practical construction of single- and multifactor portfolios as they indicate that investor type-level flow information can be a valuable input into the portfolio construction process, and thus may be a building block of an overlay strategy.

The papers most relevant to our chapter are Froot and Teo [FRO 08], Edelen *et al*. [EDE 14] and Akbas *et al*. [AKB 15]. Akbas *et al*. [AKB 15] investigate flows into mutual and hedge funds and relate them to aggregate mispricing in the stock market. They find that flows into mutual funds exacerbate aggregate mispricing while flows into hedge funds correct aggregate mispricing. In a similar study, Edelen *et al*. [EDE 14] investigate whether institutional investors tend to be on the underpriced or overpriced side of 12 well-known capital market anomaly long-short portfolios and find that they are more often on the “wrong” than on the right side. Both of these studies, however, relate aggregate mutual fund flows to styles or anomalies rather than relating style flows to style returns and risk directly. Additionally, flows are inferred from low-frequency holdings-based data rather than observed flows on a microlevel.

Froot and Teo [FRO 08] take a different approach and use transaction level data to measure institutional flows into styles directly. They assign stocks to the size, value and sector styles which allows them to measure institutional style flows. They find that style inflows positively predict returns for stocks in the same style. The study is confined to institutional investors only, however. The approach we take in this chapter is similar to [FRO 08] in that we measure flows on the style level. It differs, however, to the extent that we relate style flows to style returns. Given the richness of our data set we are also able to study other investor type flows above and beyond institutional investors. Furthermore, we also study the relationship between style flows and future style risk and illustrate the practical implications of our results.

The chapter is organized as follows. Section 7.2 introduces the data set and section 7.3 describes how style portfolios and style flows are obtained from this data set. Section 7.4 presents the main empirical results on the relationship between flows into styles and style returns and risk in a statistical setting. Section 7.5 analyzes the economic significance of the statistical results. Section 7.6 provides robustness checks and section 7.7 concludes this chapter.

7.2. Data

Our sample consists of the total daily trading flow executed through BofAML for all stocks in the S&P 500 index for the sample period running from January 2, 2014 to January 31, 2017. For each stock and day the sample contains the buy and sell US Dollar notional executed through BofAML by each of the four following client types: (i) hedge funds, (ii) institutions, (iii) retail and (iv) broker-dealers. The assignment of clients to client types follows an internal scheme based on the nature of the clients' investment activities. BofAML is a major counterparty in terms of equity flow market share. Our data set aggregates more than 1,000 individual clients. Given the comprehensive coverage of stocks and clients by BofAML, the data set is not expected to exhibit significant idiosyncrasies relative to the entire equity market flow. However, we do verify below that our sample is indeed representative of the aggregate equity market flow.

We also obtain daily factor exposures for each stock in the S&P 500 from the Axioma risk model database for the three popular investment styles: (i) value [ROS 85], (ii) momentum [JEG 93] and (iii) low volatility [ANG 06]. The factors underlying the investment style exposures employed by Axioma are given in Table 7.1. Finally, we also obtain daily returns for all stocks in the S&P 500 from the Axioma return database.

The average market share of BofAML's equity flow as a fraction of the total volume traded for all stocks in the S&P 500 on US exchanges has been around 10% over the sample period. With regard to flow composition, institutions are by far the largest investor group as measured by the fraction of investor type trading volume to total BofAML volume. On average, institutional trading volume accounts for approximately two-thirds of the total volume, followed by broker-dealers, hedge funds and retail investors who are comparable in terms of size. As broker-dealers mostly facilitate trading between the other investor type groups, we do not expect their flow to convey significant information content for style returns or risk. Consequently, we will focus on hedge funds, institutions, and retail investors in the following.

Style	Factor
Value	Average of book-to-price and earnings-to-price ratio
Momentum	Cumulative return over the last 250 trading days excluding the most recent 20 trading days
Low volatility	Average of the absolute return divided by the cross-sectional volatility of the market over the last 60 trading days

Table 7.1. *Axioma style and factor definitions*

The top panel of Figure 7.1 sheds light on the time variation in the composition of the trading flow. Specifically, it depicts the time evolution of the weights of the different investor type flows as a fraction of the total BofAML volume. We can see that the composition of the flow can vary substantially.

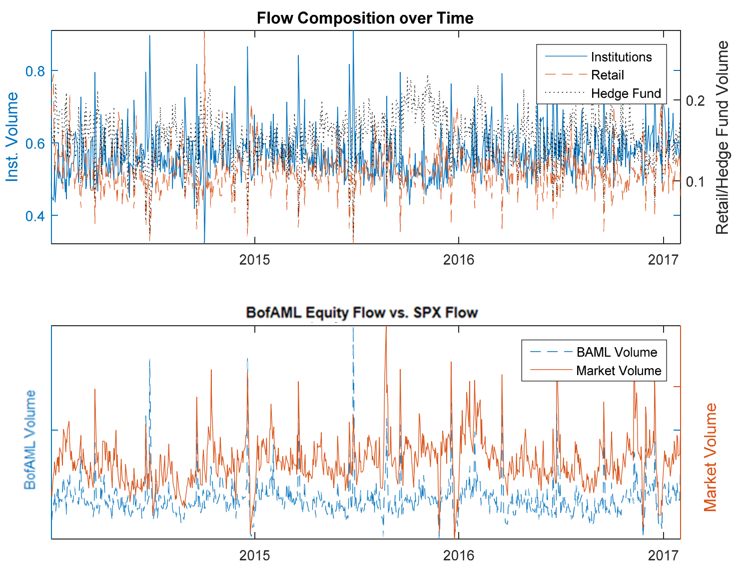

Figure 7.1. *BofAML trading flow dynamics. The top panel plots the fraction of BofAML's equity volume attributed to trading by institutions (projected on left vertical axis) as well as to retail and hedge funds (right vertical axis) over time. The bottom panel plots the BofAML equity trading volume versus the total market volume in S&P 500 stocks over time. The sample runs from January 2014 to January 2017*

In order to draw conclusions on the relationship between style flows and risk and return based on the BofAML trading flow sample, it is important to establish that there are no significant idiosyncrasies in the data set relative to the broader equity market flow. In other words, we need to ensure that our observed flow is representative of the total equity market flow. As a first characteristic, we consider the time dynamics in the total BofAML equity flow and compare it to the time variation in the S&P 500 total market flow. The bottom panel of Figure 7.1 plots the two series against each other. Reassuringly, we see that the BofAML flow is highly correlated with the total equity market flow (correlation equal to 0.735 in the sample). As a second characteristic, we consider how many of the 500 stocks in the S&P 500 are in fact traded through BofAML on every single day. On average 466 of the 500 stocks in the S&P 500 are represented in the daily BofAML flow leading us to conclude that the flow data are representative for the overall market.

7.3. Style portfolios and style flows

We construct long-only portfolios for each investment style as equally weighted top-quintile portfolios and compute their daily returns as the equally weighted return of the portfolios constituents. In particular, on the last business day of each month we sort all stocks in the considered universe by their exposure to each considered factor. Weights are assumed constant throughout each month. Stocks are assigned to quintiles and the factor portfolios are constructed by going long in an equally weighted portfolio consisting of the stocks in the top quintile[1].

Table 7.2 provides summary performance statistics for the three style portfolios. We can see that low volatility is the best performing style over the sample period earning an annualized average return of 5.73%. Momentum exhibits similar return performance albeit with higher volatility. Value had the lowest average return and highest volatility of all considered styles over the sample period.

To compute flows into styles, daily weighted net imbalances for each style portfolio are computed separately for each style and investor type. Specifically, let $w_{i,t}^{j}$ denote the time t portfolio weight of the ith stock in the portfolio for style j. The time t net imbalance of each style from investor type $k \in \{Hedge\ Fund, Institution, Retail\}$ is then computed as

$$nib_{k,t}^{j} = \sum_i w_{i,t}^{j}\, nib_{i,k,t} \qquad [7.1]$$

where $nib_{i,k,t}$ is the net imbalance of stock i from trading by investor type k on day t.

1 Axioma's volatility factor is defined such that high volatility stocks have high volatility exposure and low volatility stocks have low volatility exposure. As such, the volatility style portfolio is long the bottom quintile portfolio.

	Momentum	Value	Low volatility
Mean return (p.a.)	5.60%	4.16%	5.73%
Standard deviation (p.a.)	7.31%	8.94%	6.43%
Sharpe ratio	0.77	0.47	0.89

Table 7.2. *Style portfolio performance statistics. The annualized mean return, standard deviation and Sharpe ratio for each style is reported. The sample runs from January 2014 to January 2017*

7.4. Style flows, returns and risk: a statistical perspective

We study the interactions between style trading flows, returns and risk in a regression setting. We first focus on the relation between trading flow and style returns on both an aggregate and a cross investor type level. We then investigate how style flows are related to the risk of investing in the styles.

7.4.1. *Style flows and returns*

In order to analyze how aggregate style flows are related to factor returns, we estimate the following predictive regression model separately for each investment style

$$r^j_{t,t+h} = c + \beta x_{t-h,t} + \epsilon_{t+h} \qquad [7.2]$$

where $r^j_{t,t+h}$ denotes the h-period cumulative return from t to $t+h$ for the jth style portfolio. In our first specification, the predictor x_t consists of the aggregate time t cumulative trailing h-period net imbalance[2] into the style under consideration across all investor types. We estimate equation [7.2] for periods h equal to 1 day, 1 week and 1 month using overlapping data. t-statistics using standard ordinary least squares (OLS) as well as Newey and West [NEW 87] HAC-adjusted standard errors are reported. In this context, the lag length for the HAC correction is determined using the plug-in procedure suggested in [NEW 94] setting the lag equal to $l^* = \left\lfloor (4T/100)^{2/9} \right\rfloor$, where T is the number of observations in the sample.

A remark is in order at this point. Given the restrictions imposed by the relatively short length of our sample, tests for the significance of coefficients in a predictive regression such as equation [7.2] may exhibit relatively low statistical power. It is for that reason that we employ overlapping data to enhance the statistical power of

2 In all regression analyses, we z-score cumulative net imbalances prior to employing them in predictive regressions.

our tests. Section 7.6 provides robustness checks assessing to what extent our baseline results are sensitive toward this choice.

Table 7.3 presents the estimation results for the three considered investment styles and different forecast horizons (panels A–C). We can see that for forecast horizons of up to 1 week coefficient estimates are positive for momentum and low volatility and negative for value. However, none of the estimates is statistically significantly different from zero implying that there is no significant predictive relationship between past aggregate style flow and future returns at short-term horizons.

	Momentum	Value	Low volatility
Panel A: One-day ahead forecasts			
c	2.22E-04	1.69E-04	2.28E-04
t-Stat	1.34	0.84	1.57
t-HAC	1.45	0.83	1.70
$nib^{j}_{t-h,t}$	4.95E-05	–8.84E-05	4.01E-05
t-Stat	0.30	–0.44	0.28
t-HAC	0.19	–0.37	0.17
Adj. R^2	–0.001	–0.001	–0.001
Panel B: One-week ahead forecasts			
c	1.12E-03	8.66E-04	1.16E-03
t-Stat	3.12	1.85	3.73
t-HAC	1.70	0.96	2.00
$nib^{j}_{t-h,t}$	2.17E-04	–3.07E-04	2.38E-05
t-Stat	1.36	–1.55	0.17
t-HAC	0.79	–0.86	0.10
Adj. R^2	0.001	0.002	–0.001
Panel C: One-month ahead forecasts			
c	4.52E-03	4.03E-03	5.06E-03
t-Stat	7.32	4.75	8.79
t-HAC	3.04	1.94	3.60
$nib^{j}_{t-h,t}$	4.66E-04	1.36E-03	4.88E-04
t-Stat	3.65	8.97	4.13
t-HAC	1.65	3.81	1.90
Adj. R^2	0.017	0.098	0.021

Table 7.3. *Style returns and aggregate style flows. The table reports the estimation results for equation [7.2]. Forecasting horizons of 1 day, 1 week and 1-month are considered (panels A–C). The sample runs from January 2014 to January 2017. Overlapping daily data are used and OLS t-statistics (t-Stat) and Newey–West t-statistics (t-HAC) are provided*

This is markedly different for the 1-month forecast horizon case in panel C. All coefficients for the aggregate cumulative net imbalance impact on future returns are positive and statistically significant. Adjusted R^2 are sizeable ranging from 0.02 for momentum to 0.1 for value pointing at potential economic significance of the predictability in returns.

We now turn to analyzing the relationship between future style returns and style flows generated by *different* investor types and estimate the following variant of the predictive regression model above

$$r_{t,t+h}^{j} = c + \beta_{HF} nib_{HF,t-h,t}^{j} + \beta_{INST} nib_{INST,t-h,t}^{j} + \beta_{RET} nib_{RET,t-h,t}^{j} + \epsilon_{t+h} \qquad [7.3]$$

where subscripts HF, $INST$ and RET index the time t h-period trailing cumulative style imbalances for investor types hedge funds, institutions and retail, respectively. As previously, the model is estimated for forecasting horizons equal to 1 day, 1 week and 1 month (panels A–C) using overlapping data.

The estimation results are presented in Table 7.4. As a first observation, we can see that coefficient estimate signs vary by investor type and style. This finding particularly holds for short-term forecast horizons of up to 1 week and is in contrast to the results relating aggregate net imbalances to future returns in Table 7.3. Furthermore, adjusted R^2s are substantially improved compared to the case where aggregate imbalances are used as a predictor. This underlines the importance of analyzing the differential effects of factor flows by different investor types as the flow information content appears to vary by investor type. This result extends the evidence on the relationship between investor type specific single stock flows and stock returns, which has been documented to depend on the investor type [BOE 06]. Consistent with the results on aggregate imbalances, investor type specific factor flows are insignificant predictors of future returns for short-term horizons of up to 1 week.

	Momentum	Value	Low volatility
Panel A: One-day ahead forecasts			
c	0.00	0.00	0.00
t-Stat	1.34	0.83	1.57
t-HAC	1.42	0.83	1.65
$nib_{HF,t-h,t}^{j}$	2.05E-04	–1.68E-04	–3.50E-05
t-Stat	1.23	–0.83	–0.24
t-HAC	1.06	–0.76	–0.27
$nib_{INST,t-h,t}^{j}$	–1.42E-05	–6.09E-05	2.10E-07

t-Stat	–0.09	–0.30	0.00
t-HAC	–0.05	–0.25	0.00
$nib^{j}_{RET,t-h,t}$	1.97E-04	–8.25E-05	2.44E-04
t-Stat	1.19	–0.41	1.68
t-HAC	1.35	–0.34	1.53
Adj. R^2	0.000	–0.003	0.000
Panel B: One-week ahead forecasts			
c	0.00	0.00	0.00
t-Stat	3.12	1.85	3.73
t-HAC	1.70	0.97	2.00
$nib^{j}_{HF,t-h,t}$	–2.47E-04	3.12E-04	1.19E-04
t-Stat	–1.72	1.77	0.98
t-HAC	–1.12	1.28	0.65
$nib^{j}_{INST,t-h,t}$	2.19E-04	–2.30E-04	8.30E-05
t-Stat	1.35	–1.13	0.59
t-HAC	0.79	–0.67	0.33
$nib^{j}_{RET,t-h,t}$	9.87E-05	–3.04E-04	–2.27E-04
t-Stat	0.81	–2.18	–2.34
t-HAC	0.45	–1.09	–1.32
Adj. R^2	0.005	0.009	0.004
Panel C: One month-ahead forecasts			
c	0.00	0.00	0.01
t-Stat	7.64	5.23	9.46
t-HAC	3.24	2.16	3.90
$nib^{j}_{HF,t-h,t}$	4.60E-04	1.14E-03	2.31E-05
t-Stat	4.12	8.41	0.22
t-HAC	1.81	4.02	0.10
$nib^{j}_{INST,t-h,t}$	6.39E-04	1.01E-03	2.53E-04
t-Stat	5.22	6.65	2.16
t-HAC	2.59	2.97	0.90
$nib^{j}_{RET,t-h,t}$	–4.67E-04	5.76E-04	5.06E-04
t-Stat	–6.18	6.92	7.73
t-HAC	–2.83	2.60	3.96
Adj. R^2	0.093	0.191	0.088

Table 7.4. *Style returns and investor-level style flows. The table reports the estimation results for equation [7.3]. Forecasting horizons of 1 day, 1 week and 1 month are considered (panels A–C). The sample runs from January 2014 to January 2017. Overlapping daily data are used and OLS t-statistics (t-Stat) and Newey–West t-statistics (t-HAC) are provided*

Focusing on the 1-month forecast horizon case in panel C, we can see that results are different. Hedge fund and institutional flows are found to be significantly positive predictors of future momentum and value returns. Retail flow is found to be informative as well and is negatively related to future momentum returns and positively related to future value and low volatility returns. Adjusted R^2 are large and lie between 0.09 for low volatility and 0.19 for value. This is consistent with and extends the findings of Froot and Teo [FRO 08]. They find a positive relationship between institutional flow into the value style and future returns of value stocks while we find a positive relationship between institutional flow into the value style and future value *style returns*. This indicates that there may be significant value in exploiting style flows as a trading signal, which we will explore in section 7.5.

7.4.2. *Style flows and style risk*

In this section, we analyze the relationship between style flows and risk. Analogously, to the case of style returns in the previous section, we employ a regression setting and first focus on the relationship between aggregate style flows and style risk.

We measure the jth style's risk by the realized 1-month standard deviation of its daily returns

$$\sigma_{t,t+21}^{j} = \sqrt{\frac{1}{20}\sum_{t=1}^{21}\left(r_t^j - \overline{r^j}\right)^2} \qquad [7.4]$$

where $\overline{r^j}$ denotes the 1-month average return of style j.

We then first estimate the following regression linking aggregate time t style net imbalances to future realized volatility for each style

$$\sigma_{t,t+21}^{j} = c + \beta x_{t-21,t} + \epsilon_{t+21} \qquad [7.5]$$

where predictor x_t consists of the aggregate time t 21-day cumulative net imbalance of style j; overlapping data are used.

Table 7.5 reports the estimation results along with coefficient OLS and Newey–West t-statistics. We can see that there is a significantly negative relationship between aggregate style net imbalances and future style volatility. This holds for all considered investment styles. The finding that aggregate net flows positively predict style returns but negatively predict style volatility is consistent with leverage-type effects [BLA 76], which point to a negative correlation between returns and volatility[3].

	Momentum	Value	Low volatility
c	–2.75E+00	–2.59E+00	–2.88E+00
t-Stat	–213.16	–166.14	–212.56
t-HAC	–83.25	–63.94	–83.34
$nib^{j}_{t-21,t}$	–1.37E-02	–1.55E-02	–1.42E-02
t-Stat	–5.13	–5.55	–5.10
t-HAC	–1.80	–2.39	–2.40
Adj. R^2	0.033	0.039	0.033

Table 7.5. *Aggregate style flows and risk. The table reports the estimation results for equation [7.5]. A forecasting horizon of 1-month is considered. The sample runs from January 2014 to January 2017. Overlapping daily data are used and OLS t-statistics (t-Stat) and Newey–West t-statistics (t-HAC) are provided*

As documented for the case of predicting style returns, the predictive information content of style flows can vary by the investor type generating the flow. As such, it is natural to explore whether similar investor type specific effects also exist in the case of predicting style volatility. To address, this question we next estimate the following predictive regression model using overlapping data

$$\sigma^{j}_{t,t+21} = c + \beta_{HF} nib^{j}_{HF,t-21,t} + \beta_{INST} nib^{j}_{INST,t-21,t} + \beta_{RET} nib^{j}_{RET,t-21,t} + \epsilon_{t+21} \qquad [7.6]$$

separately for each style j where the notation follows equation [7.3]. The estimation results are reported in Table 7.6.

Interestingly, we can see that consistent with the relationship between aggregate net imbalances and style risk only institutional flow negatively predicts future style volatility. The relationship between hedge fund flow and volatility is largely insignificant while retail flow is positively related to future momentum volatility.

3 Black [BLA 76] documents an inverse relationship between stock returns and volatility. Our results suggest that positive aggregate style flows are associated with high future style returns and low volatility (and vice versa) over the 1-month forecast horizon. This is consistent with the presence of leverage effects on the style level.

Analogously to the return prediction case, employing more granular investor type level flows yields improved adjusted R^2s, which range from 0.04 for low volatility to 0.08 for momentum attenuating the increased information content contained in investor-specific flows.

	Momentum	Value	Low volatility
c	–2.75	–2.59	–2.88
t-Stat	–218.42	–167.28	–212.93
t-HAC	–85.91	–64.45	–83.18
$nib^{j}_{HF,t-h,t}$	–2.34E-04	3.86E-03	–3.66E-03
t-Stat	–0.10	1.48	–1.46
t-HAC	–0.05	0.57	–0.70
$nib^{j}_{INST,t-h,t}$	–1.65E-02	–1.80E-02	–1.54E-02
t-Stat	–6.38	–6.17	–5.40
t-HAC	–2.29	–2.88	–2.44
$nib^{j}_{RET,t-h,t}$	7.67E-03	1.52E-03	2.07E-03
t-Stat	4.79	0.95	1.30
t-HAC	2.28	0.42	0.55
Adj. R^2	0.081	0.054	0.040

Table 7.6. *Investor-level style flows and style risk. The table reports the estimation results for equation [7.6]. A forecasting horizon of 1-month is considered. The sample runs from January 2014 to January 2017. Overlapping daily data are used and OLS t-statistics (t-Stat) and Newey–West t-statistics (t-HAC) are provided*

Another important finding that is apparent from the results in Table 7.6 is that the signs of the estimated coefficients for predicting 1-month volatility are largely consistent with a negative correlation between returns and volatility. Times of high volatility are typically associated with negative returns. In cases where a significant negative predictive relationship exists for 1-month volatility, we find a negative predictive relationship for 1-month returns (Table 7.4, panel C) and vice versa.

7.5. Economic significance

Our empirical results so far show that net flows into styles are able to predict future style returns and risk. In this section, we analyze the economic significance and implications of these results. In particular, we design simple single and multifactor timing strategies based on the predictive relationships documented in the previous section. Effectively, we use the in-sample results to identify flow-based timing signals and then back test them over the entire sample. While we do acknowledge that conducting a true pseudo out-of-sample experiment would be desirable, we acknowledge the limitations induced by the data availability in our sample, which place a true out-of-sample study outside the scope of this chapter.

7.5.1. *Single-factor strategies*

We first focus on the case of managing the exposure to a single style. As 1-month return predictability and volatility predictability results have been found to be consistent with each other in the previous section, we base our trading strategies on the flow-return predictive relationship documented in section 7.4. In particular, our strategies take unit exposure to the style if the relevant trailing 1-month cumulative flow for a given investor type indicates positive returns for that factor going forward; otherwise a zero exposure is chosen. We implement this strategy separately for each investor-type flow. Additionally, a composite signal is considered that takes unit exposure to the factor if either one of the single investor type signals is indicating unit exposure and zero otherwise. Table 7.7 summarizes the trading rules. The selected exposure is chosen at the beginning of each month and held for 1 month; we also consider holding periods of 2 and 3 months.

Style	Hedge fund 1-month cumulative flow		Institutions 1-month cumulative flow		Retail 1-month cumulative flow	
	>0	<0	>0	<0	>0	<0
Momentum	Unity	Zero	Unity	Zero	Zero	Unity
Value	Unity	Zero	Unity	Zero	Unity	Zero
Low volatility	Unity	Zero	Unity	Zero	Unity	Zero

Table 7.7. *Summary of style allocation rules*

We evaluate the performance of our flow-based strategies against two benchmarks. The first benchmark is a dynamic volatility-weighted factor strategy as in [BAR 15] and [MOR 17]. This strategy increases its exposure to the considered style when style volatility is expected to be low and decreases it when it is expected to be high relative to a prespecified target volatility level. As an estimate for expected style volatility, we use the trailing 1-month volatility of the respective style portfolio and set the target volatility level equal to the unconditional sample volatility of the respective flow-based strategy. The second benchmark is a simple price momentum strategy that is based on the trailing 1-month cumulative return of the style portfolio. In particular, this strategy takes unit exposure to the style if its trailing 1-month cumulative return is positive and zero exposure otherwise.

Tables 7.8–7.11 report performance metrics for all three considered styles using all flow signals introduced above. Performance metrics for the flow-based strategies are reported at the top of each table and the performance metrics for their respective volatility-managed benchmarks are reported below. Table 7.11 also reports performance metrics for the price momentum based benchmarks for every style. The annualized average return, annualized standard deviation, return skewness, expected shortfall assuming a value-at-risk threshold of 5% and the Sharpe ratio are reported for each strategy. *P*-values for the null of equal mean returns and Sharpe ratios for the flow-based and volatility-managed strategies against the alternative of a higher mean return and Sharpe ratio for the flow-based strategy are provided as well[4]. Additionally, for the flow-based and price momentum based strategies we provide two turnover-related metrics. First, we define the investment intensity as the percentage of periods the strategy takes unit exposure to the style. Second, we define the number of switches as the number of periods the strategy changes its exposure from unity to zero or vice versa.

We first focus on the case of 1-month holding periods. From the first set of columns, we can see that incorporating flow information in style timing can significantly improve the performance of dynamically managed single factor portfolios. For instance, incorporating 1-month cumulative retail or institutional investor flow information for the momentum style increases the Sharpe ratio by 0.35 and 0.2, respectively, compared to their volatility-managed counterparts and outperforms the simple price momentum based benchmark. This is consistent with the predictability results presented earlier; retail (institutional) momentum flow has strong predictive negative (positive) power for momentum returns and volatility. Interestingly, incorporating hedge fund flows into the style timing decision process does not improve the performance of the momentum style relative to the volatility-managed benchmark despite a significant predictive relationship for future momentum returns. One possible explanation for this finding is that while 1-month hedge fund momentum flows significantly predict momentum returns, they do not

4 The distribution of the difference in Sharpe ratios is obtained via bootstrap using 1,000 resamples.

significantly predict volatility. This is contrary to institutional and retail momentum flows and could constitute a detracting driver of the performance of hedge fund momentum flows-based timing strategies. While the Sharpe ratio improvements for flow-based momentum strategies are economically significant, the null of equal Sharpe ratios of the flow-based strategies and their volatility-managed benchmarks cannot be rejected at conventional confidence levels.

For value strategies incorporating flow information into style timing yields large Sharpe ratio improvements for all investor type flows as well as for the composite signal. In fact, combining retail, hedge fund and institutional flow signals yields the highest Sharpe ratio of all considered value strategies equal to 1.35, which is more than three times as high as its volatility or price momentum managed counterpart. The improvement is a result of substantially higher average return, lower volatility and less downside risk as proxied by the improved expected shortfall and return skewness. This improvement in Sharpe ratios turns out to be statistically significant as well as indicated by the *P*-value of 0.02.

Finally, using retail flow to time the low volatility style doubles the Sharpe ratio relative to its volatility-managed benchmark and outperforms the price momentum signal. Similarly, the composite version of the low volatility strategy outperforms both its volatility-managed and price momentum based benchmark. This is again consistent with the predictability evidence presented in the previous section where retail flow was the only flow type found to significantly predict low volatility returns. However, as in the case of momentum the large improvement in economic significance does not translate into statistical significance in the considered sample.

A further crucial observation is that the investment intensity for the composite strategies is substantially higher than for the single investor type strategies. This is important as it implies that flow-based signals are not perfectly correlated across investor types which give rise to time-varying informativeness of investor-type specific style flows.

As the holding period increases, we can see that in most cases the performance of the flow-based style timing strategies deteriorate. This applies to the absolute Sharpe ratios but is particularly true for the relative outperformance vs. the volatility-managed benchmark. In most cases, Sharpe ratios of the flow-based timing strategies are similar to or less than those of the volatility-managed benchmarks if moving to a holding period of 2 or 3 months depending on the flow type and style involved.

	Rebalancing = 1 month			Rebalancing = 2 months			Rebalancing = 3 months		
	Momentum	Value	Low volatility	Momentum	Value	Low volatility	Momentum	Value	Low volatility
Flow based									
Mean return (p.a.)	3.35%	6.75%	2.02%	2.10%	6.24%	2.63%	2.74%	1.29%	3.67%
P-value	0.85	0.36	0.43	0.88	0.27	0.98	0.92	0.83	0.84
SD (p.a.)	5.16%	6.66%	4.06%	3.62%	6.60%	3.53%	4.61%	5.91%	3.86%
Skewness	–0.46	–0.42	–1.05	0.59	–0.57	–0.57	–0.28	–1.06	–0.53
ES (5%)	–0.88%	–1.07%	–0.72%	–0.58%	–1.08%	–0.58%	–0.76%	–1.01%	–0.61%
Sharpe ratio	0.65	1.01	0.50	0.58	0.95	0.74	0.60	0.22	0.95
P-value	0.52	0.13	0.74	0.42	0.10	0.41	0.48	0.54	0.32
Investment intensity	44.44%	41.67%	36.11%	23.53%	41.18%	35.29%	45.45%	36.36%	45.45%
Number of switches	14	13	12	6	11	6	7	3	5
Volatility managed									
Mean return (p.a.)	3.88%	3.09%	3.86%	1.70%	2.09%	2.57%	3.05%	2.10%	3.24%
SD (p.a.)	5.98%	7.67%	4.81%	4.29%	7.73%	4.10%	5.59%	7.84%	4.63%
Skewness	–0.56	–0.50	–0.58	–0.81	–0.76	–0.91	–0.58	–0.52	–0.68
ES (5%)	–0.93%	–1.17%	–0.74%	–0.69%	–1.19%	–0.63%	–0.89%	–1.26%	–0.74%
Sharpe ratio	0.65	0.40	0.80	0.40	0.27	0.63	0.55	0.27	0.70

Table 7.8. *Performance of single style timing strategies. The table reports performance statistics for single style timing rules a based on hedge fund flow implied signals. The bottom part of report performance metrics for volatility-managed benchmarks for each flow-based strategy in the top part of the table. Holding periods equal to 1, 2 and 3 months are considered. P-values for testing the null of an equal flow-based Sharpe ratio (mean return) relative to the volatility-managed benchmark Sharpe ratio (mean return) against the alternative of a higher Sharpe ratio (mean return) for the flow-based strategy are provided. Bootstrapping with 1,000 resamples is employed to obtain the distribution of differences in Sharpe ratios. The sample runs from January 2014 to January 2017*

	Rebalancing = 1 month			Rebalancing = 2 months			Rebalancing = 3 months		
	Momentum	Value	Low volatility	Momentum	Value	Low volatility	Momentum	Value	Low volatility
Flow based									
Mean return (p.a.)	4.90%	6.78%	5.16%	3.41%	3.03%	1.96%	2.48%	–0.66%	1.48%
P-value	0.38	0.22	0.41	0.39	0.58	0.90	0.95	0.48	0.57
SD (p.a.)	4.91%	6.31%	3.16%	5.04%	6.11%	1.93%	5.39%	6.03%	2.34%
Skewness	–0.27	–0.70	0.57	–0.65	–1.04	1.00	–0.43	–1.06	0.79
ES (5%)	–0.80%	–1.03%	–0.46%	–0.85%	–1.03%	–0.25%	–0.92%	–1.06%	–0.37%
Sharpe ratio	1.00	1.07	1.63	0.68	0.50	1.02	0.46	–0.11	0.63
P-value	0.24	0.12	0.11	0.26	0.32	0.29	0.61	0.78	0.51
Investment intensity	55.56%	44.44%	25.00%	58.82%	52.94%	11.76%	54.55%	36.36%	9.09%
Number of switches	9	17	12	4	11	3	6	6	2
Volatility managed									
Mean return (p.a.)	3.01%	2.51%	3.20%	1.64%	1.49%	2.26%	2.36%	1.36%	3.11%
SD (p.a.)	4.66%	6.24%	4.00%	4.14%	5.54%	3.62%	4.35%	5.09%	4.45%
Skewness	–0.56	–0.50	–0.58	–0.81	–0.76	–0.91	–0.58	–0.52	–0.68
ES (5%)	–0.72%	–0.95%	–0.61%	–0.66%	–0.85%	–0.56%	–0.69%	–0.82%	–0.71%
Sharpe ratio	0.65	0.40	0.80	0.40	0.27	0.62	0.54	0.27	0.70

Table 7.9. *Performance of single style timing strategies. The table reports performance statistics for single style timing rules a based on retail flow implied signals. The bottom part of report performance metrics for volatility-managed benchmarks for each flow-based strategy in the top part of the table. Holding periods equal to 1, 2 and 3 months are considered. P-values for testing the null of an equal flow-based Sharpe ratio (mean return) relative to the volatility-managed benchmark Sharpe ratio (mean return) against the alternative of a higher Sharpe ratio (mean return) for the flow-based strategy are provided. Bootstrapping with 1,000 resamples is employed to obtain the distribution of differences in Sharpe ratios. The sample runs from January 2014 to January 2017*

	Rebalancing = 1 month			Rebalancing = 2 months			Rebalancing = 3 months		
	Momentum	Value	Low volatility	Momentum	Value	Low volatility	Momentum	Value	Low volatility
Flow based									
Mean return (p.a.)	3.46%	5.72%	1.60%	1.37%	4.78%	1.73%	2.34%	1.81%	3.01%
P-value	0.95	0.46	0.53	0.76	0.48	0.85	0.75	0.95	0.61
SD (p.a.)	4.02%	5.42%	3.37%	3.49%	4.73%	3.11%	3.58%	3.84%	3.71%
Skewness	–0.61	0.25	–0.06	–0.23	0.27	–0.01	–0.54	0.33	0.02
ES (5%)	–0.70%	–0.83%	–0.57%	–0.62%	–0.76%	–0.54%	-0.61%	–0.64%	–0.60%
Sharpe ratio	0.86	1.06	0.48	0.39	1.01	0.56	0.65	0.47	0.81
P-value	0.38	0.17	0.70	0.51	0.13	0.56	0.46	0.40	0.45
Investment intensity	27.78%	38.89%	36.11%	23.53%	41.18%	29.41%	18.18%	27.27%	45.45%
Number of switches	12	13	16	8	9	6	4	3	4
Volatility managed									
Mean return (p.a.)	4.04%	2.93%	3.00%	2.49%	1.93%	1.39%	3.28%	2.14%	1.96%
SD (p.a.)	6.23%	7.27%	3.75%	6.26%	7.15%	2.24%	6.01%	7.99%	2.81%
Skewness	–0.56	–0.50	–0.58	–0.81	–0.76	-0.91	–0.58	–0.52	–0.68
ES (5%)	–0.97%	–1.11%	–0.57%	–1.01%	–1.10%	–0.34%	–0.95%	–1.29%	–0.45%
Sharpe ratio	0.65	0.40	0.80	0.40	0.27	0.62	0.55	0.27	0.70

Table 7.10. *Performance of single style timing strategies. The table reports performance statistics for single style timing rules a based on institutional flow implied signals. The bottom part of report performance metrics for volatility-managed benchmarks for each flow-based strategy in the top part of the table. Holding periods equal to 1, 2 and 3 months are considered. P-values for testing the null of an equal flow-based Sharpe ratio (mean return) relative to the volatility-managed benchmark Sharpe ratio (mean return) against the alternative of a higher Sharpe ratio (mean return) for the flow-based strategy are provided. Bootstrapping with 1,000 resamples is employed to obtain the distribution of differences in Sharpe ratios. The sample runs from January 2014 to January 2017*

	Rebalancing = 1 month			Rebalancing = 2 months			Rebalancing = 3 months		
	Momentum	Value	Low volatility	Momentum	Value	Low volatility	Momentum	Value	Low volatility
Flow based									
Mean return (p.a.)	7.49%	10.25%	6.64%	5.38%	8.23%	4.76%	4.14%	3.13%	7.16%
P-value	0.30	0.08	0.54	0.36	0.08	0.59	0.97	0.87	0.35
SD (p.a.)	6.85%	7.58%	5.40%	5.97%	7.62%	4.63%	6.37%	7.05%	5.49%
Skewness	-0.39	–0.35	–0.60	-0.30	–0.45	–0.36	-0.34	–0.61	–0.28
ES (5%)	-1.00%	–1.16%	–0.87%	-0.94%	–1.18%	–0.75%	-0.99%	–1.12%	–0.84%
Sharpe ratio	1.19	1.35	1.23	0.90	1.08	1.03	0.65	0.44	1.31
P-value	0.08	0.02	0.15	0.13	0.02	0.23	0.39	0.34	0.07
Investment intensity	80.56%	72.22%	75.00%	70.59%	76.47%	58.82%	81.82%	63.64%	81.82%
Number of switches	8	12	16	4	8	7	3	4	4
Volatility managed									
Mean return (p.a.)	4.75%	3.52%	5.17%	2.82%	2.41%	3.38%	3.42%	2.50%	4.64%
SD (p.a.)	7.30%	8.73%	6.40%	7.07%	8.92%	5.39%	7.73%	9.35%	6.59%
Skewness	-0.56	–0.50	–0.58	-0.81	–0.76	–0.91	-0.58	–0.52	–0.68
ES (5%)	-1.13%	–1.33%	–0.98%	-1.13%	–1.38%	–0.83%	-1.22%	–1.50%	–1.05%
Sharpe ratio	0.65	0.40	0.81	0.40	0.27	0.63	0.55	0.27	0.70
Price momentum									
Mean return (p.a.)	–1.50%	3.75%	3.94%	–3.13%	5.16%	6.46%	1.20%	0.97%	1.21%
Std (p.a.)	7.29%	9.04%	6.46%	7.31%	9.18%	6.50%	7.32%	9.28%	6.55%
Skewness	–0.18	–0.09	0.04	–0.22	–0.19	–0.06	–0.20	–0.19	–0.11
ES (5%)	–1.07%	–1.30%	–0.90%	–1.11%	–1.34%	–0.92%	–1.08%	–1.37%	–0.96%
Sharpe ratio	–0.21	0.42	0.61	–0.43	0.56	0.99	0.16	0.10	0.19
Investment intensity	22.22%	11.11%	27.78%	17.65%	41.18%	52.94%	27.27%	9.09%	9.09%
Number of switches	15	17	19	9	6	6	7	7	7

Table 7.11. *Performance of single style timing strategies. The table reports performance statistics for single style timing rules a based on composite investor type flow implied signals and based on a price momentum signal (bottom part of table). The middle part of the table reports performance metrics for volatility-managed benchmarks for each flow-based strategy in the top part of the table. Holding periods equal to 1, 2 and 3 months are considered. P-values for testing the null of an equal flow-based Sharpe ratio (mean return) relative to the volatility-managed benchmark Sharpe ratio (mean return) against the alternative of a higher Sharpe ratio (mean return) for the flow-based strategy are provided. Bootstrapping with 1,000 resamples is employed to obtain the distribution of differences in Sharpe ratios. The sample runs from January 2014 to January 2017*

7.5.2. *Multifactor strategies*

We now turn to multifactor strategies to investigate whether the single factor timing ability of style flows also carries over to a setting in which multiple factors are combined in a portfolio. To this end, we construct multifactor portfolios based on the flow signals developed in the previous section. In particular, we include every style with a flow-based indicator to take unity exposure in the portfolio and equal-weight the multifactor portfolio across all included styles. We apply this selection/weighting scheme separately for hedge fund, retail and institutional flows as well as the composite signal utilizing all client type flows. To evaluate the performance of the flow-based multifactor strategies we compare them to a volatility-managed version of an equal weighted multifactor strategy. This strategy increases the exposure to an equal-weighted portfolio *in all three* styles when the volatility of this portfolio is low and decreases its exposure when the volatility high. Analogously, to the single style volatility-managed portfolios expected volatility is estimated using trailing 1-month realized volatility and target volatility is set equal to the unconditional sample volatility of the respective flow-based strategy.

The performance statistics for the flow-based multifactor strategies and their benchmarks are reported in Table 7.12. Alongside, the standard performance metrics previously reported in the single factor case the average number of included styles (strategy utilization) as well as the number of changes in the multifactor portfolio are reported. We can see that all versions of the flow-based multifactor strategies exhibit a higher mean return and lower volatility translating into Sharpe ratios, which can be more than double that of their volatility-managed benchmarks. Downside risk is also reduced relative to the benchmark as evidenced by the improved skewness and expected shortfall statistics. The most favorable risk-return trade-off is achieved when combining the composite flow signal with the multifactor approach that generates a Sharpe ratio equal to 1.47 and is found to be statistically significantly larger than the Sharpe ratio of the volatility-managed benchmark. It is also worth noting that this strategy on average invests in about 2.3 strategies at any point in time that implies that is on average relatively diversified across the considered factors.

Turning to the case where holding periods longer than 1-month are considered the multifactor strategy performance deteriorates as the holding period increases. Interestingly, however, all flow-based strategies except for the retail-flow-based version are still able to outperform their volatility-managed benchmarks. This suggests that the information contained in hedge fund and institutional flows may be more permanent than the information contained in retail flow.

	Rebalancing = 1 month				Rebalancing = 2 months				Rebalancing = 3 months			
	Hedge funds	Institutional	Retail	Composite	Hedge funds	Institutional	Retail	Composite	Hedge funds	Institutional	Retail	Composite
Panel A: Flow based												
Mean return (p.a.)	4.02%	3.58%	5.61%	8.12%	3.64%	2.62%	2.80%	6.11%	2.57%	2.39%	1.09%	4.80%
P-value	0.58	0.61	0.16	0.057	0.33	0.59	0.16	0.03	0.42	0.97	0.22	0.09
SD (p.a.)	4.08%	3.44%	3.85%	5.52%	3.55%	2.90%	3.48%	5.03%	3.59%	2.58%	3.57%	5.33%
Skewness	–0.52	0.32	–0.11	–0.35	–0.43	0.51	–0.58	–0.38	–0.48	–0.29	–0.65	–0.48
ES (5%)	–0.68%	–0.51%	–0.60%	–0.83%	–0.55%	–0.44%	–0.56%	–0.76%	–0.55%	–-0.41%	–0.61%	–0.81%
Sharpe ratio	0.98	1.04	1.46	1.47	1.03	0.90	0.81	1.22	0.71	0.92	0.30	0.90
P-value	0.19	0.24	0.04	<0.01	0.09	0.24	0..03	<0.01	0.14	0.41	0.04	0.01
Strategy Utilization	1.22	1.03	1.25	2.28	1.00	0.94	1.24	2.06	1.27	0.91	1.00	2.27
Number of changes	23	21	21	21	14	11	12	11	8	6	8	7
Panel B: Volatility managed												
Mean return (p.a.)	2.94%	2.47%	2.77%	4.00%	1.69%	1.38%	1.66%	2.40%	2.13%	1.53%	2.12%	3.18%
SD (p.a.)	4.86%	4.09%	4.58%	6.57%	4.22%	3.45%	4.13%	5.97%	4.51%	3.25%	4.49%	6.70%
Skewness	–0.56	–0.56	–0.56	–0.56	–0.92	–0.92	–0.92	–0.92	–0.68	–0.68	–0.68	–0.68
ES (5%)	–0.76%	–0.64%	–0.71%	–1.02%	–0.66%	–0.54%	–0.65%	–0.94%	–0.73%	–0.53%	–0.73%	–1.09%
Sharpe ratio	0.61	0.60	0.61	0.61	0.40	0.40	0.40	0.40	0.47	0.47	0.47	0.47

Table 7.12. *Performance of multifactor strategies. The table reports performance statistics for multifactor factor timing rules a based on different investor type flow implied signals (panel A; left to right). Panel B reports performance metrics for volatility-managed benchmarks for each flow-based strategy. Holding periods of 1, 2 and 3 months are considered. P-values for testing the null of an equal flow-based Sharpe ratio (mean return) relative to the volatility-managed benchmark Sharpe ratio (mean return) against the alternative of a greater Sharpe ratio (mean return) for the flow-based strategy are provided. Bootstrapping with 1,000 resamples is employed to obtain the distribution of differences in Sharpe ratios. The sample runs from January 2014 to January 2017*

	Momentum	Value	Low volatility
	Panel A: Predicting returns		
C	0.00	0.00	0.01
t-Stat	1.96	1.24	1.98
t-HAC	2.71	1.56	2.86
$nib^{j}_{HF,t-h,t}$	3.93E-04	9.96E-04	1.14E-04
t-Stat	0.83	1.68	0.22
t-HAC	1.09	1.40	0.22
$nib^{j}_{INST,t-h,t}$	8.92E-04	5.53E-04	4.57E-04
t-Stat	1.81	0.96	0.79
t-HAC	2.20	1.33	0.83
$nib^{j}_{RET,t-h,t}$	–2.41E-04	4.82E-04	5.17E-04
t-Stat	–0.75	1.56	2.03
t-HAC	–1.43	1.57	2.71
Adj. R^2	0.03	0.13	0.07
	Panel B: Predicting volatilities		
c	–2.75	–2.57	–2.88
t-Stat	–45.30	–35.65	–43.57
t-HAC	–44.36	–24.43	–40.80
$nib^{j}_{HF,t-h,t}$	4.15E-03	1.07E-02	–8.99E-03
t-Stat	0.36	0.81	–0.67
t-HAC	0.45	0.81	–0.79
$nib^{j}_{INST,t-h,t}$	–1.62E-02	–4.18E-03	–3.74E-03
t-Stat	–1.37	–0.33	–0.25
t-HAC	–1.39	–0.54	–0.25
$nib^{j}_{RET,t-h,t}$	1.20E-02	4.77E-04	2.45E-03
t-Stat	1.56	0.07	0.37
t-HAC	2.16	0.09	0.40
Adj. R^2	0.04	–0.06	–0.07

Table 7.13. *Regression analysis using non-overlapping data. The table reports the estimation results for equation [7.3], (panel A) and equation [7.6], (panel B). A forecasting horizons of 1 month is considered. The sample runs from January 2014 to January 2017. Non-overlapping daily data are used and OLS t-statistics (t-Stat) and Newey–West t-statistics (t-HAC) are provided*

7.6. The effect of using non-overlapping data

Given the relatively short length of our sample, overlapping data are employed in the baseline regression analysis in section 7.4 to increase the statistical power of our tests. However, using overlapping data in predictive regressions can induce serial correlation in the error term which, even when using standard HAC corrections, may not be fully remedied [HOD 92, ANG 06]. In order to assess the extent to which our predictability results may be subject to an overlapping data problem, we reestimate equations [7.3] and [7.6] using non-overlapping data. The results are reported in Table 7.13 for forecast horizons of 1 month. From panel A, it becomes apparent that, as expected given the reduced statistical power due to a much lower number of observations, some of the predictive relationships between flows and returns are no longer significantly different from zero. However, there is still significant predictive power in institutional flow for momentum returns, hedge funds flow for value returns and retail flow for low-volatility returns. Importantly, the results are qualitatively similar to what we obtain in the setting where overlapping data are used with coefficients exhibiting the same signs.

Turning to the case of predicting volatilities in panel B, we can see that the deterioration in statistical significance is more pronounced than in the returns prediction case when moving from overlapping to non-overlapping data. The only significant relationship that prevails when using non-overlapping data is the retail investors' flow ability to predict momentum volatility. Similarly to the returns forecasting case, however, qualitatively the results remain broadly unchanged.

7.7. Conclusions

In this chapter, we provide a direct analysis of trading flows into the investment styles momentum, value and low volatility, and their relationship to future style returns and risk. To this end, we utilize a unique data set, which is comprised of daily trading flow data for US stocks executed through Bank of America Merrill Lynch. This data set allows us to distinguish trading by hedge funds, institutions and retail clients and investigate style trading behavior and style returns and risk separately for different types of investors. We attribute investor type flows to styles and relate style level net imbalances to future style returns and risk.

We find that style level imbalances are significantly positively related to future style returns. The exception is retail investor net imbalances into the momentum style, which predict negative momentum returns going forward. We also find a significant, albeit weaker, relationship between style net imbalances and future volatility. We use the identified relationships between net imbalances and returns to develop simple style timing and allocation rules and implement them to assess the economic significance of the relationship between net imbalances and style returns and risk. Single and multifactor approaches are considered and we find that employing style level flow information in style timing and allocation decisions can improve Sharpe ratios by as much as three times relative to simple volatility-managed benchmarks. As flow-based timing signals are found to be somewhat independent across investor types combining signals from different types of investors proves to be particularly effective. As such, cross-investor type style flow information may be used as an overlay indicator in constructing style portfolios.

7.8. Bibliography

[AKB 15] AKBAS F., ARMSTRONG W.J., SORESCU S. *et al.*, "Smart money, dumb money, and capital market anomalies", *Journal of Financial Economics*, vol. 118, no. 2, pp. 335–382, 2015.

[ANG 06] ANG A., BEKAERT G., "Stock return predictability: is it there?", *The Review of Financial Studies*, vol. 20, no. 3, pp. 651–707, 2006.

[ANG 06] ANG A., HODRICK R., XING Y. *et al.*, "The cross-section of volatility and expected returns", *The Journal of Finance*, vol. 61, no. 1, pp. 259–299, 2006.

[BAR 03] BARBERIS N., SHLEIFER A., "Style investing", *Journal of Financial Economics*, vol. 68, pp. 161–199, 2003.

[BAR 15] BARROSO P., SANTA-CLARA P., "Momentum has its moments", *Journal of Financial Economics*, vol. 116, pp. 111–120, 2015.

[BLA 76] BLACK F., "Studies of stock price volatility changes," *Proceedings of the 1976 Meetings of the American Statistical Association*, pp. 171–181, 1976.

[BOE 06] BOEHMER E., WU J., Order flow and prices, Working Paper, 2006.

[CHO 04] CHORDIA T., SUBRAHMANYAM A., "Order imblalance and individual stock returns: theory and evidence", *Journal of Financial Economics,* vol. 72, no. 3, pp. 485–518, 2004.

[EDE 16] EDELEN R.M., INCE O.S., KADLEC G.B., "Institutional investors and stock return anomalies", *Journal of Financial Economics*, vol. 119, no. 3, pp. 472–488, 2016.

[FRO 08] FROOT K., TEO M., "Style investing and institutional investors", *Journal of Financial and Quantitative Analysis*, vol. 43, no. 4, pp. 883–907, 2008.

[HOD 92] HODRICK R., "Dividend yields and expected stock returns: alternative procedures for inference and measurement", *The Review of Financial Studies*, vol. 5, no. 3, pp. 357–386, 1992.

[JEG 93] JEGADEESH N., TITMAN S., "Returns to buying winners and selling losers: implications for stock market efficiency", *The Journal of Finance*, vol. 48, no. 1, pp. 65–91, 1993.

[KEL 10] KELLEY E.K., TETLOCK P.C., "How wise are crowds? Insights from retail orders and stock returns", *Journal of Finance*, vol. 68, no. 3, pp. 1229–1265, 2010.

[KYL 85] KYLE A., "Continuous auctions and insider trading", *Econometrica*, vol. 53, pp. 1315–1336, 1985.

[LAK 92] LAKOSHINOK J., SHLEIFER A., VISHNY R., "The impact of institutional trading on stock prices", *Journal of Financial Economics*, vol. 32, pp. 23–34, 1992.

[MOR 17] MOREIRA A., TYLER M., "Volatility managed portfolios", *Journal of Finance*, forthcoming, (2017).

[STO 78] STOLL H.R., "The supply of dealer services in securities markets", *Journal of Finance*, vol. 33, pp. 1133–1151, 1978.

8

Investment and Profitability: A Quality Factor that Actually Works

8.1. Introduction

Multifactor investing popularized by the moniker "smart beta" is becoming a dominant framework in the indexing community. Several popular factors such as value, size, momentum, low beta and illiquidity are reasonably well defined and have been thoroughly explored in both academic and practitioner literature. One of the factors that attracts a lot of attention is "quality". MSCI, FTSE, Standard and Poor's and Deutsche Bank, among others, offer "quality" factor indices for investors to replicate, which is a good indication of "quality" factor popularity. "Quality" factor is believed to provide an independent source of return and is sought after as a diversifier along other popular factors due to its supposedly low or negative correlation with other factors such as value[1].

The interesting part is that all of the products that we listed above are based on very different definitions. Unlike some of the other factors, "quality" factor lacks a universally accepted level of definition and exploration in the literature (at least exploration directly under the label quality). This raises the question of the robustness and legitimacy of "quality" as a factor. This chapter is a survey of the

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1 Perhaps, another reason for interest in "quality" factor stems from interest in "growth" investing. To a degree, smart beta is an attempt to provide in the low-cost, transparent solutions strategies previously implemented by active managers. Investors traditionally categorize active managers into styles: value, small cap, etc. One of these styles is "growth" – where active managers select companies with the high growth potential. Quality factor is an attempt to map the "growth" style into the factor framework. Continuity from the active investing is partly responsible for popularity of "quality" factor.

approaches to quality adopted in popular product offerings with the goal to study their robustness.

Commercially available "quality" index simulations invariably show outperformance (at least in the relatively short time periods for which they are provided). As we pointed out earlier, the "quality" factor is not uniformly defined. The multiplicity of definitions of "quality" creates possibility (and perhaps a temptation) to data mine for the best possible outcome that makes a simple comparison of the index performance an unreliable estimate of what to expect on the forward looking basis[2].

The possibility of data mining can severely bias the back-tested performance upwards. Is there a way to identify and potentially undo the data-mining bias? There are multiple articles that raise the issue of factor robustness as well as discuss possible ways to correct for the potential data-mining bias[3]. In this chapter, we will use the framework suggested by Hsu *et al*. [HSU 15] (further HKV methodology). Their methodology is a three-step process to determine robustness of a factor:

1) factor should be sufficiently explored in peer reviewed publications;

2) factor should be robust to variations in time-periods and geographies;

3) factor should be robust to perturbations in definitions.

We will use this framework to review the definitions of "quality" in the existing index product offerings. The goal is to answer the question which, if any or all, definitions of "quality" have a reasonably strong back-up by the theoretical and empirical evidence.

We are not the first to have applied the HKV methodology to study factors and quality factor. In particular, Beck *et al*. [BEC 16] have examined a broad collection of factors including quality and their conclusion was that quality factor as a broad category lacks robustness. The difference of this study compared to Beck *et al*. [BEC 16] is that we focus specifically on the categories favored by the

2 Definitions encompass a number of measures roughly selecting "better" companies – companies may be of high quality based on multiple dimensions: profitability, margins, solvency, past growth, distress and many more. Within each of these categories there is a further definition of exact variables. For example, profitability could be measured as ROE, ROA, gross profits-to-assets ratio, profits from operations-to-book ratio, etc.

3 Among others the issues of data mining in factor robustness were raised by: Lo and MacKinlay [LO 90]; Black [BLA 93]; MacKinlay [MAC 95]; McLean and Pontiff [MCL 16], Harvey, Liu and Zhu [HAR 16], Hsu, Kalesnik and Viswanathan [HSU 15]; and Beck, Hsu, Kalesnik and Kostka [BEC 16]. Bailey, Borwein, Lopez de Prado, and Zhu [BAI 17] and Harvey and Liu [HAR 15] offered stricter statistical criteria for validating new factors as the potential remedy to correct for data mining.

practitioners. Further, we provide additional analysis of the underlying categories within quality treating categories as individual factors to test if the individual categories are robust or not.

There are several quality-related studies that we will leave out from our study. This list includes Campbell *et al*. [CAM 08], Piotroski and So [PIO 12] and Asness and Frazzini [ASN 15]. These articles are similar in that they combine a number of metrics (more than 9 each[4]) to form a composite measure. The approach of combining several measures has a certain merit – combination can arguably provide a better signal on the company overall "quality" compared to any one individual definition. The downside of the combination approach is that it creates an additional venue for data mining. Novy-Marx [NOV 16] among others points out that combining several uncorrelated measures with no statistical significance but positive in-sample returns can easily lead to a back test with strong statistical significance and no basis for outperformance in the future. Unfortunately, HKV methodology is not well suited to study robustness of combining multiple measures, beyond maybe one or two, as it requires considering too many combinations of factor perturbations. In a nutshell, combining several measures has merits and drawbacks; given that the framework that we apply in this chapter is not well suited for these quality definitions we leave them outside of the scope of this study.

8.1.1. Robustness of existing "quality" factor product offering categories

Several major index providers offer "quality" indices for investors to replicate. In Table 8.1, next to each product provider we list the variables used to define "quality" factor. Given that the exact choice of the variables may be subject to data-mining bias it is important to identify the broader group of variables that the measure is supposed to represent. For example, return-on-equity ratio is supposed to represent company profitability, debt-to-equity ratio represents company capital structure, etc. – in the table we mark the corresponding broader quality category next to each variable used by index providers.

In total we have five categories in-common between product providers to define quality:

– profitability;

– earnings stability;

4 More specifically Campbell, Hilscher, Szilagyi [CAM 08] has 10, Piotroski and So [PIO 12] has 9 and Asness and Frazzini [ASN 14] has 21 quality measures.

– capital structure;

– growth in profitability;

– accounting quality.

Index provider	Measures defining quality	Corresponding broader quality category
MSCI	Return on Equity	Profitability
	Debt to Equity	Capital Structure
	EPS Growth	Growth in Profitability
S&P	EPS Growth	Growth in Profitability
	DPS Growth	Growth in Profitability
	EPS Stability	Earnings Stability
	DPS Stability	Earnings Stability
FTSE	Return on Assets	Profitability
	Change in Asset Turnover	Growth in Profitability
	Debt to Cash Flows	Capital Structure
	Accruals	Accounting Quality
Deutsche Bank	Return on Invested Capital	Profitability
	Accruals	Accounting Quality

Table 8.1. *Popular "quality" factor index definition*

How robust are these categories together and each on its own merit in generating superior performance? Let us apply the three-step HKV methodology to answer these questions.

8.2. Literature review

The first step in the HKV methodology is a literature review. When a factor is thoroughly explored in the literature it ensures that multiple highly trained economists have examined its merits. Further, it helps to rule out the possibility that the results are a result of coding error or a glitch in the security database[5]. Let us review the literature on each of the categories listed above.

8.2.1. *Profitability (and investment)*

Profitability is quite popular as a definition of quality – it shows up in three out of four indices. There are at least seven top-tier recent academic publications which

5 It is surprising how many published results cannot be replicated – see Bailey *et al*. [BAI 17] for details.

study profitability and report that there is a premium associated with higher profitability companies. Many of the publications related to profitability are also exploring the investment factor – which is explored in a similar number of articles as profitability. For this reason we will discuss both profitability and investment in this subsection.

The Fama and French [FAM 06] article exploring profitability is motivated by valuations theory. Their valuation based argument starts with a Gordon growth model[6] to derive an equation showing the relationship between book-to-market ratio, profitability, investment and stock return:

$$\frac{M_t}{B_t} = \frac{\sum_{\tau=1}^{\infty} E(Y_{t+\tau} - dB_{t+\tau})/(1+r)^{\tau}}{B_t}$$

The valuation equation demonstrates that stock return should be proportional to book-to-market ratio and profitability and inversely proportional to investment. If the book-to-market of the firm and the investment are fixed the expected return should be proportional to the expected profitability. They also show that if the book-to-market and the profitability are fixed, the expected return should be inversely proportional to investments that the firm makes. The relationship that Fama and French derive is an accounting identity and it can be consistent with both risk-based and mispricing interpretations. One drawback that we see with Fama and French's motivation is that they study the marginal effect of profitability while keeping book-to-market and investments fixed. What if in the sample of companies, for example, the book-to-market negatively co-varies with profitability to exactly offset the effect or even to push it in the opposite direction? The accounting identity would still hold but empirically profitability would pay a negative premium.

Empirically, Fama and French show that controlling for book-to-market ratio and the company investments, more profitable firms tend to have higher return (they use a version of operating profitability as their definition of profitability). Similarly they show that controlling for the other variable low investments leads to higher stock

6 Market value of a stock, M, is equal to the sum of discounted future cash flows to equity holders. Expected gross return $(1+r)$ is used as the discounting factor. Y is earnings and dB is change in book value. The difference between Y and dB estimates the free cash flow accruing to equity holders in a future date. By scaling both sides of this equality with the current book value, B; we derive the valuation equation. So, the market-to-book ratio is equal to sum of discounted future cash flows scaled by Book. Expected Y scaled by B is expected profitability and expected dB scaled by B is expected investment. Assuming current profitability and current investment are good proxies for expected profitability and expected investment, this valuation equation shows the relationship between book-to-market ratio, profitability, investment and expected stock return.

returns. In a later article [FAM 08], Fama and French confirm that profitability and low investment are associated with better return. Separately Titman, Wei and Xie [TIT 04] and Cooper, Gulen and Schill [COO 08] show that low investment is generally associated with higher returns. In [FAM 15], Fama and French offer a five factor model including profitability and investment as independent factors. In [FAM 16] they extend their sample to international data and show that the five factor model explains return quite well in most markets – Japan and Asia-Pacific region seem to be notable exceptions where the new factors do not seem to add much on top of the existing more parsimonious models.

An important recent advancement in theoretical understanding of return implication of profitability is provided by Hou *et al.* [HOU 15]. They use q-theory to offer a risk-based explanation for why profitability and investments should pay a premium. Figure 8.1 is helpful to illustrate the theory showing the relationship between profitability, investment and weighted average cost of capital, which should translate into stock return. The basic intuition of their model is that if a firm in equilibrium has high profitability and low investments it means that it faces high cost of capital (likely driven by higher riskiness of the underlying projects). If the cost of capital were to fall the firms would start investing more, expanding business and the profitability would fall. As such, firms with low profitability and high investments are associated with low cost of capital. The high or low cost of capital directly translates into high or low stock return. In their study, Hou *et al.* form portfolios based on profitability and investments and observe returns consistent with their theory (they use ROE as their measure of profitability).

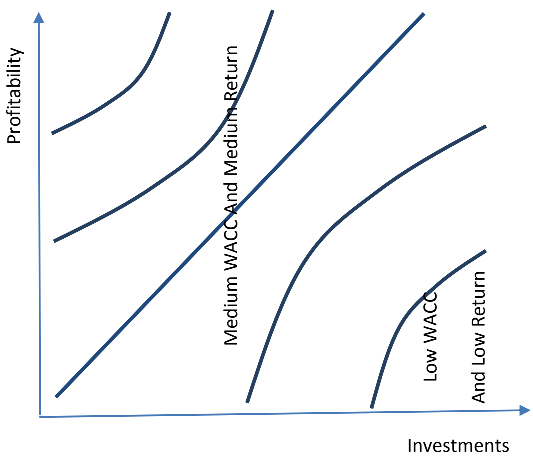

Figure 8.1. *Q-theory implied relation between profitability, investment and the cost of capital*

In [NOV 13], Novy-Marx advances a mispricing theory for profitability. He offers an explanation based on market participants' inattention to profitability. Specifically, he defines profitability as a Gross Profits-to-Assets ratio (gross profits are defined as revenues minus the costs of goods sold). He argues that gross profitability is a better proxy for future profitability as gross profits show up quite high on the earnings statement and it includes items like SG&A[7], depreciation and amortization and other items, arguably easier to be manipulated by company management. Since market participants generally lack attention and tend to focus on earnings (which don't include those arguably easier to manipulate items), gross profitability should earn a higher return. He constructs a gross profitability factor which in his sample shows return in magnitude similar to the book-to-price factor.

Recently, in [BAL 15], Ball *et al*. construct an alternative measure of profitability. They try to better match the current expenses with current revenue. Their empirical results show a stronger relationship with subsequent return compared to net income or gross profits. Their measure predicts returns as far as ten years ahead, which is somewhat hard to reconcile with the mispricing explanation.

Academic interest in profitability and investment is partly due to the fact that there are theoretical models which justify why these factors should pay a premium. Also to a large degree this interest is driven by the fact that these two factors do a very good job explaining the joint distribution of stock returns and correlations between different groups of stocks – that is why Fama and French [FAM 15] and Hou *et al*. [HOU 15] include these two factors in their parsimonious multifactor models. The empirical tests for inclusion in a mutlifactor model are motivated by Arbitrage Pricing Theory (APT) where a certain characteristic may pay a premium if it corresponds to an undiversifiable source of risk. Both profitability and investment factors help explain not only differences in returns, but are also associated with underversifiable sources of risk. Further, inclusion of these two factors in the multifactor model helps "explain" many other "anomalies" which argues that these factors capture some important underlying drivers leading to differences in returns.

To conclude there are a number of tier one academic publications which find that profitability is associated with higher stock return. They offer a risk based explanation, where in equilibrium highly profitable companies would remain profitable if they face a high cost of capital and, consequently, a high return on stock. They also offer a mispricing explanation where the premium is driven by investor lack of ability to realize persistence in profitability explained by lack of attention.

7 SG&A stands for the income statement item Selling, General and Administrative Expenses.

8.2.2. *Earnings stability*

We were able to locate two top-tier academic journal publications on earnings stability. Dichev and Tang [DIC 09] find that considerations of earnings volatility can significantly improve both short-term and long-term predictions of future earnings. Donelson and Resutek [DON 15] find that earnings uncertainty is strongly associated with overly optimistic future expectations of market analysts and investors. Note that both of these publications are in the accounting journals and do not explore the relationship of earnings stability with subsequent returns. By the HKV methodology this would be an indication of lack of premium associated with earnings stability.

8.2.3. *Capital structure*

Quality indices favor companies with low leverage. Empirical findings on the relation between corporate leverage and expected equity returns are, however, mixed, at best. Two seminal studies point out a strong and positive relation between market leverage and returns, which are Bhandari [BHA 88] and Fama and French [FAM 92]. They argue that market leverage has incremental explanatory power on expected returns on top of market beta and firm size. In [FAM 92], Fama and French also shows that controlling for market leverage, book leverage is negatively related to stock returns and overall is not very useful to explain the cross section of stock returns. More recent studies argue that book leverage is mostly negatively related to stock returns (Penman, Richardson and Tuna [PEN 07], George and Hwang [GEO 10] and Gomes and Schmid [GOM 10]).

Theoretically, the effect of leverage on return is no less mixed than the empirical evidence. Modigliani and Miller [MOD 58] proposed a very clear and strong theoretical relation between equity risk and corporate leverage. Firms with higher leverage, all else equal, have higher expected equity returns. We can view this as an increased risk to equity holders or as an equity premium that is simply being levered up, in this case a benefit. This model deliberately ignores all market frictions for simplicity, and one of them is a crucial one, which is default risk. Leverage increases expected returns to equity holders and puts more default risk on the firm. So, firms optimally adjust their leverage by trading off the cost and benefit of debt financing.

Due to the fact that leverage is inherently a strong endogenous firm characteristic, it is very demanding to build a theoretical framework to explain how it is related to expected equity returns. However, Obreja [OBR 13] offers us some economic intuition. Firms with high operating or financial leverage have a large equity risk premium. However, these firms choose to maintain a low book leverage ratio. Overall, B/M ratio helps to explain expected returns by identifying firms with high operating or high financial leverage. Book leverage is actually not useful to explain returns.

8.2.4. *Growth in profitability*

We were not able to identify any papers which study the relationship between return and profitability growth in isolation from other variables.

8.2.5. *Accounting quality*

There are at least four top-tier academic journals dedicated to the study of accounting quality. Most severe accounting manipulations are unique in nature and, thus, are hard to detect. At the same time, there are a few commonly available “set of tricks” that are easily available for managers to temporarily boost accounting measures of earnings. One way to boost earnings is to use accruals to record sales which will fail to result in actual cash-flows. [SLO 96], [HIR 04] and [CHA 06] document that firms with various accounting indicators associated with high accruals tend to have subsequent low performance. Hirshleifer *et al*. [HIR 04] attribute this to the mispricing driven by market participants focusing on headline earnings and inattention to other indications of potential low quality of the headline earnings. Furthermore, Dechow and Ge [DEC 06] confirm the higher returns associated with low accruals and observe that this is primarily driven by the investor misunderstanding the transitory nature of special items[8].

8.2.6. *Summary of the literature review*

Profitability and investment have the most papers dedicated to them. Empirical findings are non-conflicting and show a positive relation between profitability and return and a negative relation between investment and return. Accounting quality literature mostly focusing on different studies of accrual has at least four top-tier journal articles showing that high accruals are associated with lower stock returns. There are at least five articles exploring the relation between leverage and returns – the findings are conflicting and mixed. Similarly, the theoretical reasons for the relation are not unidirectional. Finally, there are no articles uniquely dedicated to exploring the relation between the growth in profitability or earnings stability and stock returns which indicates likely non-robustness of these measures.

8 Special items are non-recurrent items related to impairment charges, restructuring costs, etc. Dechow and Ge [DEC 06] argue that accruals are more likely to reflect transitory special items instead of transitory cash flows as liabilities.

8.3. Robustness across geographies and definitions

The second and third steps of the HKV methodology are to test factor robustness to test factor persistence in different geographies and to test factor robustness to perturbations in the definitions of the factor. The goal of the both of these tests is to identify a potential data-mining bias. We will combine two of these tests in this section.

Most of the empirical tests in the published works are performed on the US data. US data is the most accessible and covers a relatively long time-period (this helps with statistical significance). If a factor shows superior performance only in the US or only in a very specific time-period, it would indicate that likely this factor was a result of data mining in the first place. Examining if the factor works outside of the US is a simple way to identify the data-mining bias. In this study we will examine performance in the following five regions: US, Global Developed, Japan, Europe, and Asia Pacific excluding Japan[9].

Studying the robustness of factors to perturbations is important because researchers are looking for the strongest statistical significance of their results to put the best foot forward for their publication. Inadvertently or intentionally they may select a factor definition with the best statistical significance. One way to mitigate this tendency is to perturb the factor definition. For example, value is usually defined as price-to-book ratio in academia. But it can alternatively be defined as earnings-to-price, sales-to-price, dividend-to-price or other ratio comparing company accounting measures of size to its market valuations. If the alternative definitions which are consistent with the factor thesis show similar level of premium then this factor is robust. If not, it is likely a result of data-mining.

For the purpose of robustness tests, for each category we selected three to five definitions. In selecting various measures we were following two guidelines. First, we included measures if they are used in any of the indices or if they are reasonably popular. For instance, if ROE and ROA are both popular definitions of profitability, we would include them both. Second, we included measures with a reasonable degree of diversity within the category. For instance, we want to include measures characterizing leverage from different angles in the capital structure category. That is why we include both market and book leverage.

We use CRSP for stock returns and market capitalization and we use Compustat for company accounting information for our US tests. Similarly, we use Datastream and Worldscope to obtain return and accounting information respectively for companies in the international markets. We exclude companies with negative book

9 We follow Fama and French [FAM 16] in the choice of region specification.

values from the tests. We construct each quality measure independently using all available data for that measure.

All of our portfolios are simulated using annual rebalancing[10] at the beginning of January each year. The market capitalization is measured at the end of December of the previous year. Financials are lagged so that there are at least 6 months between the end of the fiscal year and the portfolio formation date. Following fairly standard Fama and French methodology to form portfolios, we first break the universe of stocks into the large and small groups where the US, the large group, is defined as larger than median stock by market capitalization[11] in the NYSE sample and those stocks larger than 90% by market capitalization in the international sample. All other stocks belong to the small group. For each variable we select “high” and “low” portfolios, where the former selects stocks with high characteristic in the direction pointing towards the higher quality by the underlying argument; the latter does the opposite. Within both large and small groups we select 30% of stocks using the specific “quality” measures – this gives us four groups of stocks (high and low within large and small universes) which we weight proportionally to market capitalization to form four portfolios. Finally, we equally weight the two portfolios with high (or low) “quality” characteristic from the large and small groups to form the high (or low) “quality” portfolio.

In our robustness tests for high and low “quality” portfolios, we examine three measures of performance:

1) average portfolio return difference: we test if the high portfolio outperforms the low portfolio with statistical significance. Practical importance of this test for investors is that the statistical significance would indicate that the portfolio based on this definition is likely to outperform the benchmark on a stand-alone basis. It also implies that the information ratio of this factor is likely to be reasonably high[12];

2) average Fama–French plus momentum four-factor model alphas: any given factor in isolation may not lead to outperformance (for example if either or both tests

10 Quality signals are built using annual firm financials. We acknowledge that annual rebalancing is the natural choice for rebalancing frequency for this reason.

11 Equal weighting will put excessively more emphasis on small (by market capitalization) stocks since small stocks are much more abundant than large stocks. Following standard factor construction methodology, we use capitalization weighting. We control for size by building high and low portfolios independently for small and large subgroups and by taking an equal weighted average of these. Moreover, capitalization weighting produces significantly more investible portfolios due to lower implementation costs.

12 T statistics for the return spreads between high and low portfolios can be scaled into information ratios. Specifically, information ratio is equal to the t statistic divided by the square root of time period length of the return simulation. For instance, in our tests for US, this length is 636 (months). So, monthly information ratio is equal to the t statistic divided by the square root of 636.

(1) and (3) are statistically insignificant). However, if the factor is sufficiently negatively correlated with the existing factors believed by many to be robust and represented in the four factor model[13], the positive multifactor alpha of this factor would indicate that this factor can deliver strong diversification benefits from inclusion into the multifactor portfolio. In this case investors should expect improved information and Sharpe ratios from the multifactor portfolio. The opposite is also true. A factor may show better performance in tests (1) and (3) but if the benefit of this factor is subsumed by other factors, then this factor is redundant.

3) Sharpe ratios: we test if the Sharpe ratio of the high "quality" portfolio is significantly higher than that of the low "quality" portfolio. Practical importance of this test is that it captures not just performance but also the risk characteristics of the factor. For some investors risk-reduction may be just as valuable a feature of a factor as the improved performance.

We report in Table 8.2 the results of the robustness tests for the six "quality" factor categories conducted in four regions (US, Europe, Japan and Asia Pacifica excluding Japan) and the global developed market. The first, observation is that quality factor taken as a broad category does not show robustness on any of the three measures of performance – return difference, multifactor alpha or Sharpe ratios. This conclusion confirms the finding of Beck *et al*. [BEC 16] with the definitions narrowed to the set of categories directly used by the index providers. Further, Beck *et al*. conduct the return difference and Sharpe ratio tests only – the multifactor tests are missing from their study. The predominant non-significant alphas for broadly defined quality means that these quality definitions likely do *not* justify the diversification benefits from inclusion of them into the multifactor portfolios.

"Quality" is a broad umbrella covering many nuanced subcategories. The lack of robustness of a randomly selected subcategory does not necessarily imply that each individual subcategory similarly lacks robustness. Next we will examine the individual "quality" categories one by one.

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13 Beck *et al*. [BEC 16] identify five non-quality related factors that are sufficiently explored in the literature (HKV step 1). These are value, momentum, size, illiquidity and low beta. Value and momentum are shown to be robust across definitions and geographies (HKV step 2 and 3). Size is interestingly not robust either across definitions or geographies. The paper presents mixed evidence for illiquidity, where it is robust across definitions but not across geographies.
The low beta factor is overall robust if we look at only Sharpe Ratio of the factor return. However, low beta factor premium is statistically insignificant, even though it is economically large. The reason for this outcome is the large negative correlation of this factor with the equity market (market factor) and its low absolute risk character.

Panel A
United States, 1963 - 2016

	Factor Return Premium							Sharpe Ratio			
Profitability	**High**	**Low**	**Tstat**	**SGN?**	**Alpha**	**Tstat**	**SGN?**	**High**	**Low**	**Tstat**	**SGN?**
Operating Profitability	12.81%	7.66%	2.22	Yes	3.68%	2.57	Yes	0.48	0.13	5.21	Yes
Gross Profitability	12.81%	9.95%	2.34	Yes	4.84%	5.13	Yes	0.45	0.31	1.62	No
Return on Equity	11.97%	8.63%	1.21	No	2.94%	2.09	Yes	0.43	0.17	4.21	Yes
Return on Assets	11.85%	7.98%	1.60	No	3.72%	2.84	Yes	0.42	0.14	4.90	Yes
Return on Invested Capital	12.07%	8.35%	2.12	Yes	3.16%	2.31	Yes	0.41	0.17	3.43	Yes
Earnings Stability											
Stability of EPS	10.63%	12.54%	-2.57	No	-0.30%	-0.43	No	0.35	0.44	-1.37	No
Stability of DPS	10.26%	12.05%	-0.34	No	-0.05%	-0.06	No	0.25	0.47	-4.07	No
Stability of Profitability	11.09%	10.79%	-0.41	No	-1.23%	-1.46	No	0.41	0.30	2.51	Yes
Stability of Cashflow Profits	11.55%	10.09%	0.21	No	0.08%	0.07	No	0.44	0.25	3.43	Yes
Stability of Margins	11.46%	10.65%	0.32	No	1.66%	2.14	Yes	0.41	0.31	2.90	Yes
Capital Structure											
Total Leverage	10.60%	11.53%	-1.13	No	-0.10%	-0.11	No	0.33	0.37	-0.41	No
Debt to Equity	11.21%	10.89%	0.52	No	3.48%	3.26	Yes	0.33	0.36	-0.86	No
Financial Leverage	8.89%	10.77%	-0.56	No	1.04%	0.97	No	0.19	0.36	-2.74	No
Growth in Profitability											
LT Change in ROA	11.86%	11.62%	-0.10	No	0.41%	0.48	No	0.41	0.36	1.40	No
LT Change in ROE	12.28%	11.10%	0.74	No	1.02%	1.14	No	0.44	0.33	2.56	Yes
ST Change in Asset Turnover	12.93%	9.85%	4.17	Yes	1.95%	2.96	Yes	0.45	0.27	4.42	Yes
YoY Change in DPS	12.04%	11.67%	0.37	No	1.24%	1.54	No	0.44	0.41	0.63	No
YoY Change in EPS	12.27%	11.24%	1.03	No	1.37%	2.06	Yes	0.45	0.36	2.65	Yes
Accounting Quality											
Accruals	12.27%	10.48%	1.56	No	2.93%	3.27	Yes	0.43	0.32	1.72	No
Accruals2	11.91%	9.61%	3.59	Yes	1.38%	2.33	Yes	0.40	0.27	3.62	Yes
Net Operating Assets	13.12%	8.58%	5.06	Yes	3.18%	3.76	Yes	0.47	0.22	4.44	Yes
Earnings Smoothness	11.74%	12.36%	-0.87	No	-1.52%	-2.26	No	0.41	0.45	-0.68	No
ST Change in Accruals	12.61%	10.60%	2.99	Yes	1.57%	2.48	Yes	0.43	0.32	3.02	Yes

Panel B
Global Developed, 1990 - 2016

	Factor Return Premium							Sharpe Ratio			
Profitability	**High**	**Low**	**Tstat**	**SGN?**	**Alpha**	**Tstat**	**SGN?**	**High**	**Low**	**Tstat**	**SGN?**
Operating Profitability	10.18%	6.14%	2.51	Yes	2.83%	2.76	Yes	0.53	0.20	4.02	Yes
Gross Profitability	11.07%	5.31%	4.24	Yes	6.69%	6.47	Yes	0.59	0.16	5.24	Yes
Return on Equity	10.02%	6.12%	2.89	Yes	4.18%	4.26	Yes	0.51	0.20	4.91	Yes
Return on Assets	10.06%	6.49%	2.48	Yes	4.67%	4.97	Yes	0.52	0.22	4.51	Yes
Return on Invested Capital	9.94%	6.04%	3.19	Yes	4.75%	4.95	Yes	0.49	0.20	4.19	Yes
Earnings Stability											
Stability of EPS	10.46%	5.79%	4.67	Yes	5.41%	7.37	Yes	0.54	0.19	5.72	Yes
Stability of DPS	8.94%	7.30%	1.27	No	3.71%	4.04	Yes	0.36	0.32	-0.02	No
Stability of Profitability	8.16%	8.56%	-0.70	No	-1.92%	-2.36	No	0.39	0.35	0.96	No
Stability of Cashflow Profits	8.43%	7.94%	-0.08	No	-0.64%	-0.63	No	0.42	0.30	1.51	No
Stability of Margins	8.62%	7.34%	0.86	No	1.21%	1.51	No	0.42	0.28	2.78	Yes
Capital Structure											
Total Leverage	7.83%	9.05%	-1.25	No	-0.63%	-0.73	No	0.33	0.42	-1.48	No
Debt to Equity	8.28%	7.87%	0.29	No	2.78%	3.11	Yes	0.35	0.33	0.09	No
Financial Leverage	7.44%	8.07%	-0.26	No	1.50%	1.87	No	0.29	0.35	-0.74	No
Growth in Profitability											
LT Change in ROA	9.04%	7.97%	1.15	No	1.06%	1.25	No	0.42	0.34	1.40	No
LT Change in ROE	9.33%	7.59%	1.72	No	1.65%	1.83	No	0.44	0.31	2.15	Yes
ST Change in Asset Turnover	9.52%	6.87%	3.52	Yes	1.39%	2.07	Yes	0.44	0.27	3.37	Yes
YoY Change in DPS	7.53%	8.27%	-0.86	No	-1.31%	-1.36	No	0.36	0.32	0.93	No
YoY Change in EPS	6.43%	7.69%	-1.68	No	-0.82%	-1.00	No	0.25	0.31	-0.64	No
Accounting Quality											
Accruals	9.59%	7.05%	2.25	Yes	2.84%	3.01	Yes	0.45	0.28	2.08	Yes
Accruals2	8.72%	6.98%	3.02	Yes	1.07%	2.06	Yes	0.39	0.27	3.21	Yes
Net Operating Assets	9.82%	5.99%	3.70	Yes	3.44%	3.49	Yes	0.47	0.21	3.63	Yes
Earnings Smoothness	7.39%	9.38%	-1.52	No	-3.10%	-4.01	No	0.29	0.49	-4.20	No
ST Change in Accruals	9.13%	6.95%	3.77	Yes	1.33%	2.55	Yes	0.42	0.27	3.72	Yes

Panel C
Europe, 1990 - 2016

	Factor Return Premium							Sharpe Ratio			
Profitability	**High**	**Low**	**Tstat**	**SGN?**	**Alpha**	**Tstat**	**SGN?**	**High**	**Low**	**Tstat**	**SGN?**
Operating Profitability	8.99%	6.97%	2.11	Yes	1.75%	1.97	Yes	0.38	0.25	2.41	Yes
Gross Profitability	10.69%	5.78%	4.02	Yes	5.11%	5.59	Yes	0.50	0.18	4.44	Yes
Return on Equity	10.40%	5.66%	3.37	Yes	4.87%	4.65	Yes	0.47	0.16	4.25	Yes
Return on Assets	10.71%	4.99%	3.14	Yes	5.22%	4.92	Yes	0.51	0.12	4.90	Yes
Return on Invested Capital	10.43%	5.31%	3.42	Yes	4.99%	5.17	Yes	0.47	0.14	4.45	Yes
Earnings Stability											
Stability of EPS	9.48%	6.26%	2.52	Yes	4.27%	3.98	Yes	0.40	0.20	2.78	Yes
Stability of DPS	8.42%	6.59%	1.44	No	3.33%	3.01	Yes	0.33	0.23	1.07	No
Stability of Profitability	7.87%	8.40%	-0.84	No	-1.53%	-2.08	No	0.32	0.33	-0.04	No
Stability of Cashflow Profits	7.65%	7.80%	-0.21	No	-0.88%	-0.92	No	0.29	0.29	0.03	No
Stability of Margins	9.33%	7.78%	1.44	No	1.97%	2.30	Yes	0.41	0.29	2.25	Yes
Capital Structure											
Total Leverage	7.12%	7.62%	-0.43	No	-0.12%	-0.12	No	0.25	0.28	-0.46	No
Debt to Equity	9.25%	6.18%	2.06	Yes	3.99%	4.79	Yes	0.40	0.19	3.27	Yes
Financial Leverage	7.49%	7.06%	0.12	No	1.35%	1.61	No	0.29	0.24	0.85	No
Growth in Profitability											
LT Change in ROA	10.25%	7.00%	2.66	Yes	3.00%	3.16	Yes	0.47	0.24	3.12	Yes
LT Change in ROE	9.80%	6.98%	2.32	Yes	3.21%	3.31	Yes	0.43	0.24	2.78	Yes
ST Change in Asset Turnover	9.16%	7.05%	2.74	Yes	1.18%	1.54	No	0.37	0.25	2.32	Yes
YoY Change in DPS	7.11%	7.19%	-0.37	No	0.73%	0.62	No	0.27	0.24	0.69	No
YoY Change in EPS	7.72%	6.61%	0.66	No	1.63%	1.50	No	0.31	0.22	1.56	No
Accounting Quality											
Accruals	9.26%	6.35%	1.90	No	2.91%	2.78	Yes	0.39	0.20	2.52	Yes
Accruals2	8.31%	7.34%	1.22	No	0.30%	0.40	No	0.33	0.27	1.04	No
Net Operating Assets	8.70%	6.60%	2.25	Yes	1.78%	1.97	Yes	0.34	0.23	1.65	No
Earnings Smoothness	7.53%	9.55%	-1.86	No	-2.34%	-2.59	No	0.28	0.43	-2.66	No
ST Change in Accruals	9.25%	6.92%	3.18	Yes	1.52%	2.14	Yes	0.38	0.25	2.57	Yes

Panel D
Japan, 1990 - 2016

	Factor Return Premium							Sharpe Ratio			
Profitability	**High**	**Low**	**Tstat**	**SGN?**	**Alpha**	**Tstat**	**SGN?**	**High**	**Low**	**Tstat**	**SGN?**
Operating Profitability	3.82%	0.89%	1.00	No	4.04%	1.18	No	0.04	-0.08	1.09	No
Gross Profitability	5.70%	0.07%	1.84	No	6.66%	2.31	Yes	0.13	-0.12	2.52	Yes
Return on Equity	3.30%	0.68%	0.92	No	4.28%	1.45	No	0.02	-0.09	0.95	No
Return on Assets	4.15%	-0.42%	1.45	No	5.63%	2.08	Yes	0.06	-0.14	1.85	No
Return on Invested Capital	3.70%	0.32%	1.10	No	4.56%	1.67	No	0.04	-0.11	1.36	No
Earnings Stability											
Stability of EPS	4.73%	-0.15%	1.83	No	5.09%	1.93	No	0.09	-0.13	2.55	Yes
Stability of DPS	4.56%	0.40%	2.11	Yes	4.68%	2.25	Yes	0.08	-0.12	2.45	Yes
Stability of Profitability	2.12%	3.89%	-0.96	No	-3.36%	-1.44	No	-0.03	0.05	-0.71	No
Stability of Cashflow Profits	1.18%	2.74%	-0.98	No	-2.85%	-1.31	No	-0.08	0.00	-0.59	No
Stability of Margins	1.53%	1.82%	-0.48	No	-1.35%	-1.19	No	-0.06	-0.04	-0.17	No
Capital Structure											
Total Leverage	1.55%	2.93%	-0.79	No	-2.24%	-0.80	No	-0.06	0.01	-0.40	No
Debt to Equity	2.86%	0.27%	1.05	No	2.05%	1.53	No	0.01	-0.11	2.00	Yes
Financial Leverage	1.32%	0.61%	0.60	No	1.11%	1.08	No	-0.07	-0.10	0.59	No
Growth in Profitability											
LT Change in ROA	3.02%	1.79%	0.71	No	2.12%	0.88	No	0.01	-0.05	0.45	No
LT Change in ROE	3.16%	1.03%	0.92	No	2.60%	0.99	No	0.02	-0.08	0.90	No
ST Change in Asset Turnover	3.69%	0.84%	1.41	No	3.51%	1.53	No	0.04	-0.09	1.46	No
YoY Change in DPS	1.50%	1.05%	-0.07	No	0.56%	0.43	No	-0.06	-0.08	0.44	No
YoY Change in EPS	0.64%	0.95%	-0.36	No	0.16%	0.11	No	-0.10	-0.08	-0.17	No
Accounting Quality											
Accruals	5.43%	-0.02%	1.69	No	6.31%	2.07	Yes	0.11	-0.12	2.23	Yes
Accruals2	1.90%	0.75%	1.07	No	1.29%	1.39	No	-0.04	-0.09	1.25	No
Net Operating Assets	2.35%	1.18%	0.75	No	1.71%	0.74	No	-0.02	-0.08	0.49	No
Earnings Smoothness	1.42%	2.42%	-0.56	No	-0.83%	-0.84	No	-0.06	-0.02	-1.09	No
ST Change in Accruals	1.73%	1.20%	0.61	No	0.40%	0.44	No	-0.05	-0.07	0.51	No

Panel E Asia Pacific x Japan, 1990 - 2016											
	Factor Return Premium							Sharpe Ratio			
Profitability	High	Low	Tstat	SGN?	Alpha	Tstat	SGN?	High	Low	Tstat	SGN?
Operating Profitability	11.03%	8.46%	0.70	No	6.79%	4.39	Yes	0.41	0.23	2.20	Yes
Gross Profitability	11.06%	8.02%	0.67	No	7.01%	4.14	Yes	0.42	0.21	2.68	Yes
Return on Equity	10.64%	8.15%	1.13	No	4.52%	3.45	Yes	0.37	0.23	2.28	Yes
Return on Assets	10.43%	10.61%	-0.48	No	0.50%	0.37	No	0.37	0.34	0.60	No
Return on Invested Capital	10.60%	9.65%	0.69	No	1.01%	0.67	No	0.35	0.32	0.47	No
Earnings Stability											
Stability of EPS	12.08%	7.53%	2.20	Yes	1.84%	0.88	No	0.41	0.22	1.89	No
Stability of DPS	8.97%	8.76%	0.54	No	-3.08%	-1.33	No	0.25	0.31	-0.77	No
Stability of Profitability	10.03%	8.88%	0.60	No	-1.91%	-1.12	No	0.32	0.27	0.53	No
Stability of Cashflow Profits	12.51%	9.10%	1.62	No	2.11%	1.37	No	0.46	0.27	2.63	Yes
Stability of Margins	9.85%	9.55%	-0.42	No	2.22%	1.41	No	0.35	0.28	1.34	No
Capital Structure											
Total Leverage	11.20%	10.12%	0.88	No	-0.95%	-0.68	No	0.38	0.35	0.34	No
Debt to Equity	10.28%	11.07%	-0.50	No	-1.21%	-0.74	No	0.35	0.38	-0.40	No
Financial Leverage	9.61%	11.62%	-1.30	No	-0.87%	-0.64	No	0.31	0.41	-1.45	No
Growth in Profitability											
LT Change in ROA	11.35%	10.11%	0.65	No	2.74%	1.71	No	0.41	0.34	0.85	No
LT Change in ROE	11.24%	10.40%	0.39	No	2.30%	1.36	No	0.40	0.35	0.60	No
ST Change in Asset Turnover	11.40%	7.96%	2.51	Yes	1.32%	1.08	No	0.40	0.24	2.85	Yes
YoY Change in DPS	10.98%	9.35%	0.42	No	3.77%	2.17	Yes	0.40	0.28	1.47	No
YoY Change in EPS	7.85%	10.51%	-1.57	No	-1.76%	-1.12	No	0.23	0.34	-1.33	No
Accounting Quality											
Accruals	10.58%	10.88%	-0.34	No	3.72%	2.21	Yes	0.37	0.36	0.23	No
Accruals2	10.87%	9.08%	0.79	No	0.91%	0.60	No	0.38	0.27	1.78	No
Net Operating Assets	12.43%	7.86%	2.00	Yes	5.01%	3.30	Yes	0.47	0.21	3.71	Yes
Earnings Smoothness	8.92%	11.93%	-1.49	No	-3.11%	-2.12	No	0.27	0.44	-2.55	No
ST Change in Accruals	10.67%	9.20%	1.08	No	1.12%	0.91	No	0.37	0.29	1.40	No

Table 8.2. *Robustness of quality categories used in product offerings across geographies and definitions*

8.3.1. *Profitability*

By the first measure – return difference – profitability largely brings a statistically significant return advantage only in two out of five regional groups: globally and in Europe. In other regions the return difference is mostly in the same direction but the difference lacks statistical significance. By multifactor alpha, with a few exceptions, it is statistically significant in all regions. By Sharpe ratios, profitability largely brings statistically significant improvements in three out of five regions (with the exception of Japan and the Asia Pacific region). Taken together this evidence indicates that profitability is likely to be beneficial on the risk adjusted basis and when considered in the multifactor setting. The fact that evidence based on the return difference is rather weak means that on a stand-alone basis profitability brings rather weak benefits.

8.3.2. *Earnings stability, capital structure and growth in profitability*

There is very little evidence that these factors deliver outperformance whether considered alone, in a multifactor setting or on the risk adjusted basis.

8.3.3. *Accounting quality*

Within the category the accruals based measures (including Net Operating Assets) tend to show very weak return advantage. Specifically, Net Operating Assets tend to be associated with better performance in most of the international markets. But generally, the robustness tests show extremely weak evidence in favor of this category.

8.3.4. *Summary of robustness tests*

Profitability seems to bring robust benefits on the risk-adjusted basis or on a multifactor basis; taken alone profitability may not translate into an attractive enough information ratio to be interesting for investors. Accounting quality has much weaker evidence, but different measures of accruals do tend to be associated with potential benefits albeit weak. Earnings stability, capital structure and growth in profitability have no empirical evidence to benefit investors.

The empirical evidence matches quite well with the indication that we received from surveying the literature. In the literature survey we saw the most research on profitability. We saw some research on accounting quality and more specifically on accruals. We saw very little non-contradicting research on the other three categories which indicates their non-robustness.

Based on this we would label profitability to be robust, accounting quality to be relatively robust and the remaining three, earnings stability, capital structure and growth in profitability, to be non-robust. Coming back to "quality" factor indices, what are the conclusions for the index products offered by the product providers? We repeat in Table 8.3 the index definitions from Table 8.1 and we add one additional column showing the degree of robustness associated with each category. What we observe is that most of the indices use at least a few non-robust measures in their definitions. The Deutsche Bank index seems to be the one which combines a measure of profitability with a measure of accounting quality which is likely to exhibit the most robustness out of this roster of indices.

Index Provider	Measures Defining Quality	Corresponding Broader Quality Category	Robustness of the Broader Category
MSCI	Return on Equity	Profitability	Robust
	Debt to Equity	Capital Structure	Non-Robust
	EPS Growth	Growth in Profitability	Non-Robust
S&P	EPS Growth	Growth in Profitability	Non-Robust
	DPS Growth	Growth in Profitability	Non-Robust
	EPS Stability	Earnings Stability	Non-Robust
	DPS Stability	Earnings Stability	Non-Robust
FTSE	Return on Assets	Profitability	Robust
	Change in Asset Turnover	Growth in Profitability	Non-Robust
	Debt to Cash Flows	Capital Structure	Non-Robust
	Accruals	Accounting Quality	Relatively Robust
Deutsche Bank	Return on Invested Capital	Profitability	Robust
	Accruals	Accounting Quality	Relatively Robust

Table 8.3. *Popular "quality" factor index: definition and robustness*

8.4. A more detailed examination of profitability and investment

In our robustness tests we saw that profitability tends to show the most robustness among the different ways to define quality. In our literature review we also saw that most studies considering profitability also investigate investment. The number of academic studies dedicated to investment is as high as the ones dedicated to profitability. The high number of studies dedicated to the investment factor motivate us to also consider robustness of investment in the same framework that we studied other "quality" factors.

Another reason to examine investment is that we saw measures of accounting quality showing some albeit very weak evidence of outperformance. A recent article by Stambaugh and Yuan [STA 16] clusters different anomalies into groups. One of the groups includes investment, issuance and accruals (which is the most widely used measure to capture accounting quality). If investment is a more robust measure it is logical to assume that the premium associated with accruals is subsumed by the investment factor, and, therefore, investment should be a preferred definition for practitioner use.

The theoretical arguments indicate that high investment should be associated with lower performance, and low investment should be associated with higher performance. Academic studies define investment as change in Book Value of Assets (Assets). For our robustness study we also included the change in Book Value of Equity (Book Value). We conduct our robustness study in the same regions as before and present the results in Table 8.4.

	Factor Return Premium							Sharpe Ratio			
	High	Low	Tstat	SGN?	Alpha	Tstat	SGN?	High	Low	Tstat	SGN?
United States, 1963 - 2016											
Asset Growth	13.58%	9.17%	3.65	Yes	1.91%	2.47	Yes	0.50	0.22	5.06	Yes
Book Growth	12.64%	10.17%	1.95	No	0.36%	0.46	No	0.45	0.28	3.38	Yes
Global Developed, 1990 - 2016											
Asset Growth	9.57%	5.93%	2.41	Yes	1.45%	1.70	No	0.48	0.19	3.72	Yes
Book Growth	8.84%	6.15%	1.82	No	0.93%	1.11	No	0.42	0.20	3.31	Yes
Europe, 1990 - 2016											
Asset Growth	9.49%	5.69%	2.60	Yes	1.24%	1.18	No	0.41	0.16	3.30	Yes
Book Growth	8.19%	6.01%	1.59	No	0.21%	0.22	No	0.32	0.18	2.14	Yes
Japan, 1990 - 2016											
Asset Growth	1.61%	0.58%	0.69	No	-0.43%	-0.32	No	-0.05	-0.10	0.65	No
Book Growth	1.65%	0.83%	0.53	No	-0.64%	-0.45	No	-0.05	-0.09	0.45	No
Asia Pacific x Japan, 1990 - 2016											
Asset Growth	11.41%	7.03%	1.53	No	3.57%	2.01	Yes	0.43	0.17	3.41	Yes
Book Growth	11.83%	7.60%	1.55	No	2.88%	1.56	No	0.43	0.20	2.95	Yes

Table 8.4. *Robustness of investment across geographies and definitions*

Outside of Japan, investment provides a statistically significant return advantage on the risk-adjusted basis in all regions for both variations of investment. Based on return difference, the t-stats are weaker compared to Sharpe ratio tests but it is still significant at the 5% level in all but two cases and in all cases at the 10% level. In multifactor settings investment loses its statistical significance – this is consistent with the previous findings in the literature that the investment factor is correlated with value. We shall discuss the multifactor implications of investment later in this section.

8.4.1. *Treating profitability and investment as a combined factor*

In our literature review we saw that profitability and investment are often discussed in tandem. Their joint consideration is theoretically motivated either by the valuation based argument or by the q-theory. The theory also indicates that returns should be distributed along the dimension of low profitability and high investment firms, which are supposed to have low returns, to the high profitability and low investment firms, which are supposed to have high returns.

If we were to follow the behavioral interpretation we could argue that high profitability and low investment firms are high quality firms which are supposed to generate a premium. The q-theory would argue that these firms face a higher cost of capital which should translate into high stock returns. The mispricing argument would argue that these firms are profitable, conservatively managed companies with the discipline to return earnings to equity investors instead of spending the earnings on low or negative NPV empire building projects or by directing them to company management compensation.

Both of these theories argue that profitability and investment measures are linked and should be considered together. If this interpretation is correct then the factor based on the combination of the two signals would be a more parsimonious way to define quality – investors would be dealing with one strategy built on the combination of the two factors instead of the two separate portfolios.

Let's construct a factor based on the combination of profitability and investment simply averaging the two signals. We will call it the Cost-of-Capital (COC) factor[14]. If the combined factor that we constructed contains all the information about the two factors relevant for explaining the differences in performance for stocks then individually profitability and investment factors would show no alpha in the presence of the combined COC factor. We conduct this test and show the results in Table 8.5. The results support the theoretical arguments – both RMW (profitability) and CMA (investment) factors display statistically insignificant alphas once COC factor is added to the multifactor model. We interpret this as supporting evidence that profitability and investment should be considered jointly.

United States, 1963 July - 2016 June					
	Dependent Variables				
	COC	**COC**	**COC**	**RMW**	**CMA**
Intercept	0.18%	0.10%	0.05%	0.11%	0.00%
tstat	3.11	2.46	1.48	0.95	0.07
COC				0.57	0.68
CMA		0.74	0.78		
RMW	0.16		0.20		
MKT	-0.12	-0.07	-0.03	-0.07	0.00
SMB	-0.04	-0.11	-0.04	-0.29	0.08
HML	0.38	0.04	-0.01	-0.06	0.22
WML	0.04	0.02	0.01	0.01	0.00

Table 8.5. *Redundancy test of combined profitability and investment factor in the multifactor setting*

14 We take z scores of profitability and investment measures in the cross section of stocks to make them comparable in magnitude. COC factor is built using the simple average of the profitability and investment z scores.

NOTE.– COC (cost of capital) is a factor constructed as a combination of profitability and investment averaging the point in time cross sectional z-scores of the two signals.

8.4.2. *Robustness of profitability and investment combination*

Since there is a theoretical argument for treating profitability and investment in tandem, we can apply the same HKV methodology to test the robustness of the combination of investment and profitability. The tests for the permutations of different definitions of profitability and investment are displayed in Table 8.6. With the exception of Japan the combination of profitability and investment shows very robust evidence for improved performance on all three evaluation metrics: return difference, multifactor and Sharpe ratio tests. This is a strong indication for the robustness of the combination of profitability and investment as a definition of quality.

Panel A											
United States, 1963 - 2016											
	Factor Return Premium							Sharpe Ratio			
Combined w. Asset Growth	High	Low	Tstat	SGN?	Alpha	Tstat	SGN?	High	Low	Tstat	SGN?
Operating Profitability	13.85%	8.68%	4.02	Yes	2.86%	3.66	Yes	0.55	0.19	6.36	Yes
Gross Profitability	13.72%	9.14%	4.23	Yes	5.70%	6.32	Yes	0.52	0.25	4.14	Yes
Return on Equity	13.63%	8.86%	3.60	Yes	2.45%	3.19	Yes	0.53	0.20	5.99	Yes
Return on Assets	13.22%	8.14%	3.65	Yes	4.51%	5.43	Yes	0.54	0.16	7.39	Yes
Return on Invested Capital	13.34%	9.09%	3.67	Yes	2.69%	3.44	Yes	0.51	0.22	5.67	Yes
Combined w. Book Growth											
Operating Profitability	13.58%	7.02%	4.17	Yes	4.23%	4.44	Yes	0.55	0.11	6.76	Yes
Gross Profitability	13.23%	9.93%	2.83	Yes	5.05%	5.47	Yes	0.49	0.30	2.27	Yes
Return on Equity	12.91%	8.13%	2.69	Yes	2.98%	3.37	Yes	0.52	0.16	6.25	Yes
Return on Assets	12.54%	8.24%	2.56	Yes	3.98%	4.18	Yes	0.48	0.16	6.35	Yes
Return on Invested Capital	12.50%	8.35%	3.13	Yes	3.39%	3.55	Yes	0.46	0.18	5.00	Yes
Panel B											
Global Developed, 1990 - 2016											
	Factor Return Premium							Sharpe Ratio			
Combined w. Asset Growth	High	Low	Tstat	SGN?	Alpha	Tstat	SGN?	High	Low	Tstat	SGN?
Operating Profitability	10.07%	6.44%	2.21	Yes	2.30%	2.23	Yes	0.52	0.22	3.64	Yes
Gross Profitability	11.17%	5.27%	4.43	Yes	6.87%	6.82	Yes	0.60	0.16	5.46	Yes
Return on Equity	9.80%	6.13%	2.71	Yes	3.85%	4.00	Yes	0.50	0.20	4.66	Yes
Return on Assets	10.33%	5.62%	3.86	Yes	5.51%	6.13	Yes	0.54	0.17	5.54	Yes
Return on Invested Capital	10.09%	5.93%	3.80	Yes	4.83%	5.48	Yes	0.51	0.20	4.67	Yes
Combined w. Book Growth											
Operating Profitability	10.30%	5.77%	2.83	Yes	3.37%	3.41	Yes	0.54	0.18	4.41	Yes
Gross Profitability	11.14%	5.08%	4.57	Yes	7.13%	7.08	Yes	0.60	0.15	5.56	Yes
Return on Equity	9.74%	5.77%	2.81	Yes	4.09%	4.20	Yes	0.50	0.18	4.75	Yes
Return on Assets	10.47%	5.80%	3.63	Yes	4.92%	5.09	Yes	0.55	0.18	5.57	Yes
Return on Invested Capital	10.36%	5.48%	4.51	Yes	5.33%	5.98	Yes	0.52	0.17	5.39	Yes
Panel C											
Europe, 1990 - 2016											
	Factor Return Premium							Sharpe Ratio			
Combined w. Asset Growth	High	Low	Tstat	SGN?	Alpha	Tstat	SGN?	High	Low	Tstat	SGN?
Operating Profitability	9.35%	6.34%	2.68	Yes	1.66%	1.73	No	0.40	0.21	3.02	Yes
Gross Profitability	10.89%	5.74%	4.26	Yes	5.35%	5.76	Yes	0.52	0.18	4.81	Yes
Return on Equity	10.25%	4.86%	3.87	Yes	3.63%	3.23	Yes	0.46	0.12	4.81	Yes
Return on Assets	11.28%	4.03%	4.40	Yes	5.17%	4.25	Yes	0.54	0.07	5.94	Yes
Return on Invested Capital	11.28%	4.18%	4.99	Yes	5.47%	4.92	Yes	0.53	0.08	6.03	Yes
Combined w. Book Growth											
Operating Profitability	8.59%	6.77%	1.80	No	0.90%	1.02	No	0.36	0.24	2.09	Yes
Gross Profitability	10.58%	5.66%	4.00	Yes	5.08%	5.43	Yes	0.50	0.17	4.57	Yes
Return on Equity	10.06%	4.98%	3.88	Yes	3.57%	3.20	Yes	0.45	0.12	4.46	Yes
Return on Assets	10.57%	4.91%	3.53	Yes	4.31%	3.70	Yes	0.50	0.12	5.09	Yes
Return on Invested Capital	10.77%	4.93%	4.44	Yes	4.70%	4.58	Yes	0.50	0.12	5.56	Yes

Panel D
Japan, 1990 - 2016

	Factor Return Premium							Sharpe Ratio			
Combined w. Asset Growth	**High**	**Low**	**Tstat**	**SGN?**	**Alpha**	**Tstat**	**SGN?**	**High**	**Low**	**Tstat**	**SGN?**
Operating Profitability	4.78%	1.05%	1.25	No	3.66%	1.03	No	0.08	-0.08	1.38	No
Gross Profitability	5.39%	0.48%	1.73	No	5.36%	1.90	No	0.12	-0.11	2.41	Yes
Return on Equity	3.99%	0.59%	1.32	No	2.66%	0.94	No	0.05	-0.10	1.44	No
Return on Assets	4.58%	0.07%	1.64	No	4.36%	1.64	No	0.08	-0.12	2.26	Yes
Return on Invested Capital	3.91%	0.80%	1.25	No	2.80%	1.09	No	0.05	-0.09	1.55	No
Combined w. Book Growth											
Operating Profitability	4.82%	0.37%	1.44	No	4.60%	1.38	No	0.08	-0.11	2.01	Yes
Gross Profitability	5.69%	-0.04%	1.87	No	6.50%	2.25	Yes	0.13	-0.13	2.64	Yes
Return on Equity	3.73%	0.44%	1.13	No	2.82%	0.92	No	0.04	-0.10	1.32	No
Return on Assets	4.37%	-0.59%	1.56	No	5.34%	1.93	No	0.07	-0.14	2.19	Yes
Return on Invested Capital	4.44%	0.50%	1.36	No	4.32%	1.63	No	0.08	-0.10	1.88	No

Panel E
Asia Pacific x Japan, 1990 - 2016

	Factor Return Premium							Sharpe Ratio			
Combined w. Asset Growth	**High**	**Low**	**Tstat**	**SGN?**	**Alpha**	**Tstat**	**SGN?**	**High**	**Low**	**Tstat**	**SGN?**
Operating Profitability	11.12%	7.57%	0.87	No	5.88%	3.23	Yes	0.43	0.19	2.95	Yes
Gross Profitability	11.99%	7.36%	1.22	No	8.08%	4.54	Yes	0.48	0.18	3.58	Yes
Return on Equity	10.29%	7.12%	1.14	No	2.53%	1.66	No	0.38	0.18	3.09	Yes
Return on Assets	11.20%	8.70%	1.00	No	2.38%	1.70	No	0.42	0.25	2.66	Yes
Return on Invested Capital	11.85%	8.19%	1.77	No	1.84%	1.18	No	0.43	0.23	2.79	Yes
Combined w. Book Growth											
Operating Profitability	11.05%	8.07%	0.69	No	5.61%	3.10	Yes	0.41	0.21	2.56	Yes
Gross Profitability	12.03%	8.10%	0.88	No	7.96%	4.41	Yes	0.48	0.21	3.11	Yes
Return on Equity	11.52%	8.29%	1.19	No	3.19%	2.04	Yes	0.43	0.23	2.89	Yes
Return on Assets	11.20%	8.65%	1.01	No	2.80%	2.03	Yes	0.42	0.25	2.75	Yes
Return on Invested Capital	12.42%	8.45%	1.94	No	3.11%	1.92	No	0.45	0.24	2.91	Yes

Table 8.6. *Robustness of combination of investment and profitability across geographies and definitions*

8.5. Conclusion

Quality as a category, albeit very popular in practitioner circles, lacks a widely accepted definition. When we examine the categories used in the indices to define "quality" for robustness using HKV methodology, we find that:

1) Profitability delivers superior performance on the risk adjusted and multifactor basis;

2) Accounting quality has very weak evidence to deliver superior performance;

3) Earnings stability, capital structure and growth in profitability have no robust evidence of superior performance.

Among these groups we find that profitability is examined in many academic studies; we find accruals examined in only a few academic studies; and we find very little evidence of examination of the last three categories. Given this evidence, we label profitability as robust, accounting quality as weakly robust and the other three as non-robust.

By examining the academic literature, we observe that profitability is frequently considered together with investment in the same studies. There are several theoretical arguments why high profitability low investment firms should pay a premium, one of which is that firms with such characteristics must face high costs of capital in economic equilibrium. High cost of capital should translate into the high stock return. When we consider investment and profitability jointly we find them to be quite robust across both geographies and definitions (Japan is the only region where investment does not improve performance). The combined factor constructed based on the average of the investment and profitability signals explains these two factors taken individually. Given the evidence. a combination of profitability and investment may be the preferred way to define quality from the practitioner perspective.

8.6. Appendix: Profitability and investment from multifactor perspective – a practitioner's perspective

We have seen in Table 8.4 that investment factor (with the exception of Japan) is quite robust based both on the performance and on the Sharpe ratio difference. At the same time, multifactor alphas of investment factor are not significant in the four-factor model. Does our finding imply that investors interested in multifactor solutions should ignore investment factor?

Fama and French (2014) include both investment and profitability on top of the existing three factor model (which consists of market, value and size factors) because they find that these two factors help explain the joint distribution of stock returns and correlations. Furthermore, adding these two factors helps the new model explain many of the existing documented return anomalies. They also find that Investment factor is highly correlated with value factor. Finally, Fama and French (2014) find that controlling for a shorter list of factors: market, investment, size and profitability, makes value, a very popular factor, redundant. Is that true that once multifactor investors add investment factor into their portfolios they may ignore value factor?

To help understand the importance of factors in multifactor portfolios from the practioner's point of view, we provide in Table 8.7 the premia associated with profitablity, investment and the more popular factors (value, size, momentum and market beta) measured with Fama-MacBeth regressions (Table 8.7). We also provide the correlation matrix for these factors in the Table 8.8. All factors display significant premia (with the exception of market beta – a result widely known in the literature as the flat or even slightly inverted security market line). The biggest difference with the previous results is that both investment (asset growth) and value (book-to-market) signals are helpful to forecast return. From the correlation matrix we observe that the portfolios generated by value and investment are strongly positively correlated with each other – this is why in the multifactor APT motivated models they tend to explain each other. At the same time, the fact that they do not subsume each other and both show up as strong predictors of return in the Fama-MacBeth regressions implies that both are important from the practitioner perspective as the generators of outperformance[15]. Another major insight we get from the correlation table is that investment and profitability factors are highly negatively correlated, so using both of them in a multifactor portfolio provides significant diversification benefits.

	Intercept	Size	Book to Market	Momentum	Beta	Asset Growth	Profitability
United States, 1963 - 2016							
Mean	0.96%	0.11%	0.43%	0.73%	-0.09%	-0.41%	0.54%
T-Stat	3.53	3.12	8.81	5.63	-0.77	-8.92	5.38
Global Developed, 1985 - 2016							
Mean	4.88%	0.80%	0.04%	0.39%	0.17%	-0.08%	2.01%
T-Stat	3.98	3.42	2.22	2.64	0.64	-3.04	2.30
Europe, 1985 - 2016							
Mean	1.18%	0.12%	0.14%	1.01%	-0.10%	-0.11%	0.61%
T-Stat	4.09	3.57	2.14	5.24	-0.74	-2.91	4.34
Japan, 1987 - 2016							
Mean	0.63%	0.08%	1.25%	0.13%	-0.23%	-0.12%	0.03%
T-Stat	0.90	1.30	4.95	0.47	-0.63	-0.46	0.25
Asia Pacific x Japan, 1987 - 2016							
Mean	2.35%	0.30%	0.44%	0.49%	-0.34%	-0.12%	1.17%
T-Stat	4.70	5.03	3.21	2.50	-2.06	-2.13	1.79

Table 8.7. *Premia associated with profitability, investment and the most popular factors (measured using Fama-MacBeth regressions)*

United States, 1963-2016

	SMB	HML	WML	BAB	CMA	PRF
SMB	1.00					
HML	-0.09	1.00				
WML	-0.02	-0.18	1.00			
BAB	-0.02	0.34	0.18	1.00		
CMA	-0.11	0.69	-0.01	0.32	1.00	
PRF	-0.30	-0.11	0.24	0.17	-0.07	1.00

Global Developed, 1990-2016

	SMB	HML	WML	BAB	CMA	PRF
SMB	1.00					
HML	0.03	1.00				
WML	0.13	-0.24	1.00			
BAB	0.25	0.43	0.25	1.00		
CMA	-0.03	0.72	-0.05	0.38	1.00	
PRF	-0.22	-0.30	0.31	-0.01	-0.15	1.00

Europe, 1990-2016

	SMB	HML	WML	BAB	CMA	PRF
SMB	1.00					
HML	0.01	1.00				
WML	0.08	-0.29	1.00			
BAB	0.49	0.14	0.31	1.00		
CMA	0.02	0.54	0.04	0.23	1.00	
PRF	-0.03	-0.69	0.48	0.09	-0.21	1.00

Japan, 1990-2016

	SMB	HML	WML	BAB	CMA	PRF
SMB	1.00					
HML	0.14	1.00				
WML	-0.13	-0.24	1.00			
BAB	0.26	-0.02	0.25	1.00		
CMA	0.23	0.56	-0.27	-0.07	1.00	
PRF	-0.10	-0.27	0.24	0.14	-0.40	1.00

Asia Pacific x JP, 1990-2016

	SMB	HML	WML	BAB	CMA	PRF
SMB	1.00					
HML	0.06	1.00				
WML	0.04	-0.30	1.00			
BAB	0.20	0.03	0.05	1.00		
CMA	-0.10	0.14	0.21	0.05	1.00	
PRF	-0.29	-0.55	0.20	-0.03	0.30	1.00

Table 8.8. *Correlations between profitability, investment and the most popular factors*

15 Our conclusion is closely related to Daniel and Titman [DAN 98], which argues that expected returns are related to book-to-market ratio beyond the risk factor it proxies for. Book-to-market and investment capture similar type of risks; hence factors based on them are highly correlated.

8.7. Bibliography

[ASN 14] ASNESS C.S., FRAZZINI A., PEDERSEN L.H., Quality minus junk, Working paper, AQR Capital, 2014.

[BAI 17] BAILEY D., BORWEIN J., LOPEZ DE PRADO M. *et al.*, "The probability of backtest overfitting", *Journal of Computational Finance*, vol. 20, no. 4, pp. 39-69, 2017.

[BAL 15] BALL R., GERAKOS J, LINNAINMAA J.T. *et al*., "Deflating Profitability", *Journal of Financial Economics*, vol. 117, no. 2, pp. 225–248, 2015.

[BEC 16] BECK N., HSU J., KALESNIK V. *et al.*, "Will Your Factor Deliver? An Examination of Factor Robustness and Implementation Costs", *Financial Analysts Journal*, vol. 72, no. 5, pp. 58–82, 2016.

[BHA 88] BHANDARI L.C., "Debt/equity ratio and expected common stock returns: empirical evidence", *Journal of Finance*, vol. 43, no. 2, pp. 507–528, 1988.

[BLA 93] BLACK F., "Beta and return", *Journal of Portfolio Management*, vol. 20, pp. 8–18, 1993.

[CAM 08] CAMPBELL J.Y., HILSCHER J., SZILAGYI J., "In search of distress risk", *Journal of Finance*, vol. 63, pp. 2899–2939, 2008.

[CAR 97] CARHART M., "On Persistence in Mutual Fund Performance", *Journal of Finance*, vol. 52, no. 1, pp. 57–82, 1997.

[CHA 06] CHAN K., CHAN L.K.C., JEGADEESH N. *et al.*, "Earnings quality and stock returns", *Journal of Business 79*, pp. 1041–1082, 2006.

[COO 08] COOPER M., GULEN H., SCHILL M., "Asset growth and the cross-section of stock returns", *Journal of Finance*, vol. 63, no. 4, pp. 1609–1651, 2008.

[DAN 98] DANIEL K., TITMAN S., "Characteristics or covariances?", *The Journal of Portfolio Management*, vol. 24, no. 4, pp. 24–33, 1998.

[DEC 06] DECHOW P., GE W., "The Persistence of Earnings and Cash Flows and the Roles of Special Items: Implications for the Accrual Anomaly", *Review of Accounting Studies*, vol. 11, nos. 2–3, pp. 253–296, 2006.

[DIC 09] DICHEV I.D., TANG W., "Earnings volatility and earnings predictability", *Journal of Accounting and Economics*, vol. 47, nos. 1–2, pp. 160–181, 2009.

[DON 15] DONELSON D.C., RESUTEK R.B., "The predictive qualities of earnings volatility and earnings uncertainty", *Review of Accounting Studies,* vol. 20, no. 1, pp. 470–500, 2015.

[FAM 73] FAMA E., MACBETH J., "Risk, return, and equilibrium: empirical tests", *Journal of Political Economy*, vol. 81, pp. 607–636, 1973.

[FAM 92] FAMA E., FRENCH K.R., "The Cross-Section of Expected Stock Returns", *Journal of Finance*, vol. 47, no. 2, pp. 427–465, 1992.

[FAM 93] FAMA E., EUGENE F., FRENCH K.R., "Common risk factors in the returns on stocks and bonds", *Journal of Financial Economics*, vol. 33, pp. 3–56, 1993.

[FAM 06] FAMA E., EUGENE F., FRENCH K.R., "Profitability, investment, and average returns", *Journal of Financial Economics*, vol. 82, pp. 491–518, 2006.

[FAM 08] FAMA E.F., FRENCH K.R., "Average Returns, B/M, and Share Issues", *Journal of Finance*, vol. 63, no.4, pp. 1653–1678, 2008.

[FAM 15] FAMA E., EUGENE F., FRENCH K.R., "A five-factor asset pricing model", *Journal of Financial Economics*, vol. 116, pp. 1–22, 2015.

[FAM 16] FAMA E., EUGENE F., FRENCH K.R., "Dissecting anomalies with a five-factor model", *Review of Financial Studies*, vol. 29, pp. 69–103, 2016.

[GEO 10] GEORGE T.J., HWANG C.-Y., "A resolution of the distress risk and leverage puzzles in the cross section of stock returns", *Journal of Financial Economic*s, vol. 96, no. 1, pp. 56–79, 2010.

[GOM 10] GOMES J.F., SCHMID L., "Levered returns", *Journal of Finance*, vol. 65, no. 2, pp. 467–494, 2010.

[HAR 15] HARVEY C.R., LIU Y., Lucky factors, Working Paper, Fuqua School of Business, Duke University, 2015.

[HAR 16] HARVEY C.R., LIU Y. *et al*., "…and the Cross-Section of Expected Returns", *Review of Financial Studies*, vol. 29, no. 1, pp. 5–68, 2016.

[HIR 04] HIRSHLEIFER D., HOU K., TEOH S.H. *et al.*, "Do Investors Overvalue Firms with Bloated Balance Sheets?", *Journal of Accounting and Economics*, vol. 38, pp. 297–331, 2004.

[HOU 15] HOU K., XUE C., ZHANG L., "Digesting anomalies: an investment approach", *Review of Financial Studies*, vol. 28, pp. 650–705, 2015.

[HSU 15] HSU J.C., KALESNIK V., VISWANATHAN V., "A Framework for Assessing Factors and Implementing Smart Beta Strategies", *Journal of Index Investing*, vol. 6, no. 1, 2015.

[HSU 17] HSU J., SHINGO G., GOYAL A. *et al*., "Is HML Redundant?", *Research Affiliates*, working paper, 2017.

[LO 90] LO A., MACKINLAY A.C., "Data-Snooping Biases in Tests of Financial Asset Pricing Models", *Review of Financial Studies*, vol. 3, pp. 431–468, 1990.

[MAC 95] MACKINLAY A.C., "Multifactor Models Do Not Explain Deviations from the CAPM", *Journal of Financial Economics*, vol. 38, pp. 3–28, 1995.

[MCL 16] MCLEAN R.D., PONTIFF J., "Does academic publication destroy stock return predictability?", *Journal of Finance*, vol. 71, pp. 5–32, 2016.

[MOD 58] MODIGLIANI F., MILLER M.H., "The cost of capital, corporation finance and the theory of investment", *The American Economic Review*, vol. 48, no. 3, pp. 261–297, 1958.

[NOV 13] NOVY-MARX R., "The other side of value: The gross profitability premium", *Journal of Financial Economics*, vol. 108, pp. 1–28, 2013.

[NOV 16] NOVY-MARX R., Testing Strategies Based on Multiple Signals, Working paper, 2016.

[OBR 13] OBREJA I., "Book-to-market equity, financial leverage, and the cross-section of stock returns", *The Review of Financial Studies*, vol. 26, no. 5, pp. 1146–1189, 2013.

[PEN 07] PENMAN S.H., RICHARDSON S.A., TUNA I., "The book-to-price effect in stock returns: accounting for leverage", *Journal of Accounting Research*, vol. 45, no. 2, pp. 427–467, 2007.

[PIO 12] PIOTROSKI J.D., SO E.C., "Identifying Expectation Errors in Value/Glamour Strategies: A Fundamental Analysis Approach", *Review of Financial Studies*, vol. 25, pp. 2841–2875, 2012.

[SLO 96] SLOAN R., "Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings?", *Accounting Review*, vol. 71, no. 3, pp. 289–315, 1996.

[STA 16] STAMBAUGH R.F., YUAN Y., "Mispricing Factors", *Review of Financial Studies*, vol. 30, pp. 1270–1315, 2016.

[TIT 04] TITMAN S., WEI K.C.J., XIE F., "Capital investments and stock returns", *The Journal of Financial and Quantitative Analysis*, vol. 39, no. 4, pp. 677–700, 2004.

9

Common Equity Factors in Corporate Bond Markets

Size, value, momentum and beta factors have been extensively studied for equity markets, but their impact on corporate bond markets is much less explored. Since structural models based on contingent claims link credit and equity securities, we study whether or not these factors extend their success in equity markets to US credit markets. While size, value and momentum are economically and statistically significant in the US high yield (HY) space, we find that only size and momentum have explanatory power for the US investment grade (IG) market. Finally, we combine size, value, momentum and beta to construct equal-weighted (EW), investable, long-only, multifactor portfolios and demonstrate that these portfolios outperform traditional fixed-income benchmarks on a risk-adjusted basis.

9.1. Introduction

Over the past 40 years finance theories have evolved from simple single-factor models to more complex multifactor models. Initially, the Capital Asset Pricing Model (CAPM) [SHA 64] postulated that equity markets can be described by a single factor (market beta). The basic premise of the model is that market participants require a risk premium for investing in high-beta assets that are typically considered more risky than low-beta assets.

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In the wake of the CAPM, researchers have identified other factors that reliably explain the variability of asset returns such as value [BAS 77], size [BAN 81] and momentum [JEG 93]. The development of these new factors leads to the seminal multifactor models by [FAM 92, FAM 93] and [CAR 97] that describe market dynamics more accurately and therefore have received ample attention in recent years by researchers and market practitioners alike[1]. In fact, over recent years asset managers have designed investment vehicles guided entirely by factors (e.g. value or momentum) rather than traditional metrics (e.g. sectors or regions).

In general, any variable that accurately and reliably captures a risk or return characteristic of an asset class can be considered a factor. For example, momentum has been thoroughly vetted across regions and asset classes and has been shown to exhibit explanatory power for asset returns. While factors are employed in various settings and for many different reasons, a common trait of factor-based investing is, however, to exploit one or more factors to harvest associated risk premia and benefit from diversification effects, which may ultimately lead to superior risk-adjusted returns when compared to market-capitalization weighted (MCW) (cap-weighted) benchmarks (see [ANG 14]).

For decades, investment portfolios were partitioned into one of two broad investment vehicles or a combination thereof: traditional index funds and actively managed funds. Traditional index funds are passive strategies designed to replicate indices based on conventional weighting schemes (market capitalization) that allow investors to acquire the underlying indices in a simple, transparent and cost-effective manner. By contrast, actively managed funds aim to execute specific, often more complex investment strategies, which typically lure investors with the promise of superior returns when compared to their passive counterparts, despite higher expense ratios typically associated with active portfolio management[2]. However, increased complexity in securities and regulations as well as failure of active managers to deliver on their promises allowed for a new, factor-based investment approach to emerge (see [ANG 09]). Factor-based investing aims to combine the cost-effectiveness and transparency of passive strategies with the promise of superior risk-adjusted returns of actively managed strategies[3]. By using factors, rather than traditional metrics to guide asset allocation decisions, factor-based investing offers a new investment paradigm that has profoundly changed management of equity

1 Fama and French [FAM 15] enrich their traditional three-factor model by adding operating profitability and investment, showing that the new five-factor model performs better than their original three-factor model.

2 Actively managed funds typically charge a management and/or performance fee.

3 Since risk premium, return driver and characteristic are all terms referring to variables carrying explanatory power of market dynamics (risk, return, correlation), alternative beta, smart beta, advanced beta, scientific beta, exotic beta, etc., can all be subsumed under the term factor-based investing.

portfolios. Nowadays factor-based strategies in the equity space are not only firmly grounded in academic literature but they are also implemented by many asset managers globally (see [BLA 15, p. 21]).

Despite its success in equity space and the intuitive link between holders of equity and debt (both own claims against the same underlying assets of a firm, see [MER 74]), factor-based investing in the fixed-income space is less mature. Here, we investigate if four of the most thoroughly studied and most broadly accepted equity factors (size, value, momentum and beta)[4] also offer a risk premium in US credit markets. While we find that size, value and momentum are economically and statistically significant in the US HY space, we report that only size and momentum have explanatory power for the US IG market. In addition, we investigate the performance and diversification benefits of an EW, investable, long-only, multifactor portfolio and demonstrate that higher risk-adjusted returns can be achieved by combining all four factors.

Our contribution relates to the recent literature that examines factors in credit markets and closest to our study are [ISR 16] and [HOU 17]. The key difference between these authors and us is that both examine discretionary bond-specific factor definitions, whereas we focus on well-documented equity factor definitions as well as the link between equities and corporate bonds.

The remainder of this chapter is organized as follows. In section 9.2, we highlight the shortcomings of a typical fixed-income index that simultaneously serve as motivation for why factor-based strategies could represent a promising alternative for investors. In section 9.3, we define and motivate the four factors at the heart of this analysis. The data and empirical methodology are detailed in section 9.4. Finally, we present and summarize our findings in sections 9.5 and 9.6.

9.2. Traditional indices in fixed-income markets

In 1923, the first cap-weighted index was constructed by the Standard Securities Corporation[5], which included 233 equities. Each company in this index was weighted according to its market value of outstanding shares. This very first index served as a prototype for many indices used to benchmark the performance of actively managed portfolios just a few years later. This dynamic profoundly changed active portfolio management, as deviations from benchmark portfolios, for the first time, posed additional risks (tracking error)[6] to active asset managers, leading to

4 Harvey *et al*. [HAR 16] provide an excellent summary on factor-based investing in the equity space and recount more than 300 papers on cross-sectional return patterns published in various journals.

5 Today known as Standard & Poor's.

6 Standard deviation of the active returns.

portfolio allocations that were more in line with those of their corresponding benchmark portfolios.

Moreover, investing in equities is considerably different from investing in corporate bonds. While investors in equity securities can typically rely on an unambiguous mapping between firms and corresponding equities, the ambiguous mapping between firms and their outstanding bonds frequently complicates the selection process of credit portfolios. Moreover, credit securities of a given firm frequently differ in features, indentures, covenants and most importantly in maturity and position in the capital structure, further exacerbating the selection process of credit securities. Due to these substantial differences in credit and equity securities, it is not surprising that construction algorithms for equity and credit portfolios differ profoundly as well.

Not only are the underlying asset classes of equity and credit markets fundamentally different, implications of benchmarking actively managed portfolios against cap-weighted benchmarks for each asset class are as well. First, while both equity and credit benchmarks contain a large number of securities, constituents of fixed-income indices are continuously changing due to the maturing nature of fixed-income securities, while constituents of equity indices are relatively stable. This leads to significantly higher turnover rates in fixed-income indices when compared to equity indices. Second, liquidity is much less of an issue for equity securities when compared to trading over-the-counter (OTC) corporate bonds. As a result, investing in a significant portion of credit securities of a typical credit index is infeasible due to lack of liquidity, while all constituents of equity indices are typically attainable. Lastly and most importantly, while investors tracking cap-weighted equity benchmarks typically hold large positions in large-cap firms usually associated with reduced levels of risk, cap-weighted indices in credit space push investors into the most prolific issuers of debt, which are intuitively associated with elevated levels of risk. This counterintuitive dynamic of tracking cap-weighted indices in bond markets is known as the "bums problem" [SIE 03] and leads to assigning the largest weight to those corporations (or countries) with the largest amounts outstanding in the index.

The introduction of benchmark indices, the complexities of credit securities and the counter-intuitive herding into most prolific issuers of debt in credit space are all reasons why it is difficult and suboptimal to track a cap-weighted bond index. Yet, theses dynamics in credit markets simultaneously and intuitively motivate why factor-based strategies may significantly and sustainably outperform their cap-weighted peers.

9.3. Factor investing in credit markets

Factor-based investing, in a nutshell, is the systematic identification and exploitation of sustainable risk premia existing in a given market, which when combined properly can ultimately lead to superior risk-adjusted returns. As market capitalization is rarely an attractive factor (especially in credit markets), portfolios derived from factor-based investment strategies may, and in credit markets should, deviate from traditional benchmarks significantly. Factor-based investing is a tantalizing proposition, as it allows investors to customize the risks assumed and to harvest associated risk premia. At the heart of factor-based investing is, therefore, the identification of factors via a diligent vetting process. That is, each factor should be rooted in sound economic or behavioral rationale, exhibit significant premia that are expected to persist in the future, display the same characteristics across regions and must be implementable through liquid investment vehicles (see [ANG 09] or [AME 12]). The four factors at the heart of this study meet these requirements in equity space (see [HAR 16] for a summary review of the literature). Due to structural models based on contingent claims (see [MER 74]), it stands to reason that size, value, momentum and beta factors could potentially offer risk premia in credit markets as well. Similar to [BAK 12] we ensure that quintile portfolios are not dominated by single large issuers and weigh each issuer equally rather than employing a market-capitalization weighting scheme. Accordingly, we use EW benchmarks for each segment we study.

9.3.1. *Size*

Smaller companies are typically associated with lower liquidity, higher distress and more downside risk than larger firms. Hence, smaller companies should outperform larger firms to compensate investors for taking on the additional risk (see [BAN 81]). The behavioral argument for a size premium is given by limited investor attention to smaller companies and subsequent mispricing (see [STA 12]). Here, we define size as the market capitalization of the company's equity:

$$Size_t = SO_t \times PPS_t \qquad [9.1]$$

where SO_t denotes the number of shares outstanding and PPS_t is the price per share in month t. To study size in credit markets, we construct a size factor portfolio containing the bonds of the smallest 20% of all eligible companies.

9.3.2. *Value*

[FAM 92] use the book-to-market ratio (BE/ME) as a measure of equity value. A high BE/ME is indicative of a cheap stock in relative terms while a low BE/ME signals the opposite. According to [ZHA 05] "costly reversibility of investments" rationale, companies with high sensitivity to economic shocks are inherently riskier and hence should offer a risk premium. According to behavioral finance, investors overreact (underreact) to bad (good) news and extrapolate recent price movements into the future, which results in underpricing (overpricing). Here, we adopt the [FAM 92] definition of value:

$$Value_t = \frac{BE_{t-6}}{ME_t} \qquad [9.2]$$

where BE_{t-6} and ME_t denote book equity and market equity in month $t-6$ and t, respectively. Analogous to the construction of the size factor portfolio, we devise a value factor portfolio by combining the bonds of the 20% most undervalued firms in the eligible investment universe.

9.3.3. *Momentum*

Momentum attempts to forecast future asset returns by looking at the changes in asset-specific, return-relevant variables in the past (e.g. changes in asset prices or earnings per share). The most frequently studied momentum factor in equity space is equity price momentum. The simple rationale for this factor in equity markets is that winners will keep on winning while losers will keep on loosing. [JEG 93] show that this is indeed the case by demonstrating that steady positive monthly stock returns predict future positive stock returns. [ASN 13] demonstrate an omnipresence of momentum across asset classes and regions. A behavioral explanation behind the momentum anomaly is that stock prices initially underreact to information. Conversely, prices may overreact and continue to rise above their fundamental value implicating herding behavior. Momentum is defined as:

$$Momentum_t = \frac{EP_t}{EP_{t-12}} - \frac{EQMKT_t}{EQMKT_{t-12}} \qquad [9.3]$$

where EP_t and EP_{t-12} denote equity price in month t and $t-12$, and $EQMKT_t$ and $EQMKT_{t-12}$ denote equity market in t and $t-12$, respectively. To study momentum in credit markets, we construct a quintile portfolio based on the bonds of the firms with the highest residual equity momentum.

9.3.4. *Beta*

Contrary to efficient market theory, the low-beta anomaly postulates that investors are not adequately compensated for investing in high-beta stocks. In fact, [HAU 72] and [BLA 72] find that a portfolio that is short riskier stocks against a long position in low-beta stocks generates sustainable positive returns. [FRA 14] provide an overview of possible explanations for the existence of this low-beta anomaly. These explanations range from human behavior and incentive structures to specific investment constraints, and in theory are equally applicable to corporate bond markets as well. We define beta as:

$$Beta_t = \frac{cov(r_s, r_m)}{var(r_m)} \qquad [9.4]$$

where r_m, r_s, $cov(r_s, r_m)$ and $var(r_m)$ denote the monthly stock returns of stock s, monthly market returns, covariance of monthly stock and market returns, and the variance of monthly market returns over a period of 12 months, respectively. The factor portfolio used to study beta in credit markets contains the bonds of the 20% of issuers with the lowest equity beta.

Here, we rebalance factor portfolios on a monthly basis, impose no turnover restrictions on the factor-portfolios and estimate transaction costs as a function of issue rating, maturity and total turnover associated with each factor portfolio following [CHE 07].

Due to structural models based on contingent claims, extending arguments for each of the above-mentioned factors from equity to credit space is not only intuitive but also grounded in sound academic theory (see [MER 74]), and hence studying these factors in credit space is warranted.

9.4. Data and methodology

9.4.1. *Data*

Monthly data are provided by Bank of America Merrill Lynch Global Index System (BAML) as described in [BEK 16]. The data set covers the period from December 1999 to November 2016 for US HY and IG bonds. Since factors require market data and data from financial statements, only publicly traded corporations are considered in this analysis[7]. Furthermore, we use a 6-month lag to ensure the absence of forward-looking biases in our data set (see [BHO 09]).

The total return of any credit security is predominantly driven by two components: changes in issue-relevant interest rates and changes in issuer-specific credit spreads. Only the latter component is relevant in the context of factor-based investing in credit markets, as interest rate changes are independent of the

7 Currently about half of the companies in the investment universe are publicly traded firms.

idiosyncratic components impacting the credit spread of a particular corporation. Therefore, to evaluate factor returns of credit portfolios, excess returns over duration matched sovereign bond rates (here US Treasuries) should be studied. Excess returns, which account for all defaults within the studied period and that are therefore freed of survivorship bias, are provided by BAML.

9.4.2. *Methodology*

All issuers are partitioned into an IG and a HY bond universe according to their rating to accommodate the fact that bonds with varying credit risks exhibit different market behavior (see [MER 74]) and transaction costs (see [CHE 07]). A separation that also prevails in practice as most investors are looking for either HY or IG bonds.

A common practice in the academic literature (see [BEN 97] or [FRA 14]) is to investigate the existence of factor premia via quintile analysis. That is, issuers are ranked and grouped into five quintiles according to their factor scores. Here, we adopt this approach and weigh each issuer equally to ensure that quintile portfolios are not dominated by large issuers of bonds. Accordingly, we use EW benchmarks to ensure comparability of factor and benchmark portfolios. Given the weighting scheme and monthly excess returns of each bond, the performance of each quintile for each factor portfolio and bond universe can be computed. Quintile portfolios and corresponding benchmarks are rebalanced on a monthly basis.

While we concede that long-short portfolios might lead to improved risk-adjusted returns, we focus on long-only strategies as most corporate bond investors are restricted to long-only portfolios and shorting credit-securities is not easy as it is with equity securities.

Moreover, trading OTC corporate bonds involves significantly higher transaction costs that vary in time, rating and transaction size (see [EDW 07]) when compared to trading stocks. However, existing literature either ignores transaction costs completely, assumes fixed costs (see [GEB 05] or [JOS 13]) or focuses on low turnover strategies in order to minimize transaction costs (see [AME 12]). Here, we estimate transaction costs as a function of issue rating, maturity and total turnover associated with each factor portfolio similar to [CHE 07]. Besides single-factor portfolios, we also analyze multifactor portfolios following [ISR 16].

9.5. Empirical results

9.5.1. *Comparing factor portfolio returns in credit markets*

To compare factor portfolios in credit markets, we first compute risk-adjusted returns for all factor portfolios. In addition, we regress multifactor portfolio returns on credit market excess returns and credit market excess returns with equity returns of Fama–French size, value and momentum factors to extract the alpha of multifactor portfolios in corporate bond markets. We adjust for risk in three ways:

1) Sharpe ratio (SR) in Table 9.1: Measures returns for each factor portfolio relative to its total risk:

$$SR_i = \frac{r_i}{\sigma_i} \qquad [9.5]$$

where r_i is the annual average excess return (based on monthly returns) of factor portfolio i divided by the annual average standard deviation σ_i of those returns.

2) Regression in Table 9.2, panel (A): Corrects for systematic risk of multifactor portfolio i by regressing its returns on the default premium:

$$R_{it} = \alpha_{it} + \beta_i DEF_t + \varepsilon_{it} \qquad [9.6]$$

where R_{it} is the return of the multifactor portfolio i and DEF_t is the default premium in month t. The intercept in this regression is the equivalent to the CAPM-alpha for the corporate bond market, where the default premium represents the market factor (see [HOU 17]). As we use excess returns over duration-matched Treasuries, we do not need to include the term factor.

3) Regression in Table 9.2, panel (B): Corrects for systematic risk using the default premium, equity momentum and the Fama–French three-factor model[8]. We run the following regression:

$$\begin{aligned} R_{it} &= \alpha_{it} + \beta_{i1} MKT_t + \beta_{i2} SMB_t + \beta_{i3} HML_t + \beta_{i4} UMD_t \\ &\quad + \beta_{i5} DEF_t + \varepsilon_{it} \qquad [9.7] \end{aligned}$$

where *MKT* (market), *SMB* (small minus big), *HML* (high minus low) and *UMD* (up minus down) are the equity market, equity size, equity value and the equity momentum premium, respectively.

8 Data on MKT, SMB, HML and UMD from Kenneth French's Website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

9.5.2. *Single-factor performance*

Panel (A) of Table 9.1 reports results for each of the individual factors across both segments. Average size returns are 6.01% per year in US HY and 1.73% in US IG credit markets. Value generates average returns of 6.54% (US HY) and 1.51% (US IG) compared to the market returns of 4.37% and 1.25% for the US HY and IG markets, respectively. The annualized returns for the momentum factor are 6.40% (US HY) and 2.22% (US IG). Average beta returns are 4.49% (US HY) and 1.22% (US IG). Corresponding volatilities are reported in Table 9.1.

US high yield	Market	Size	Value	Momentum	Beta
Panel (A): Top-decile risk/return					
Mean	4.37%	6.01%	6.54%	6.40%	4.49%
Volatility	9.84%	13.38%	13.40%	7.89%	9.09%
Sharpe ratio	0.44	0.45	0.49	0.81	0.49
Panel (B): Excess return					
Alpha		1.64%*	2.17%**	2.03%**	0.12%
t-stat		1.49	2.10	1.76	0.05
Tracking error		5.43%	4.92%	4.09%	2.64%
Information ratio		0.30	0.44	0.50	0.04
US investment grade					
Panel (A): Top-decile risk/return					
Mean	1.25%	1.73%	1.51%	2.22%	1.22%
Volatility	3.80%	4.41%	4.57%	3.24%	3.52%
Sharpe ratio	0.33	0.39	0.33	0.69	0.35
Panel (B): Excess return					
Alpha		0.48%*	0.26%	0.97%***	−0.03%
t-stat		1.50	0.82	4.16	0.17
Tracking error		1.37%	1.49%	0.93%	0.94%
Information ratio		0.35	0.18	1.05	−0.03

Table 9.1. *Performance summary of single-factor portfolios. Results for market, size, value, momentum and beta for the US HY as well as the US IG corporate bond market. At the beginning of each calender month, EW long-only portfolios are constructed from the 20% issuers with the highest factor exposure to equity size, equity value, equity momentum and equity beta. Statistical significance is denoted by *, ** and *** corresponding to the 90, 95 and 99% confidence levels, respectively*

Panel (B) of Table 9.1 reports statistically significant excess returns for size and momentum premia in both US credit segments. Value, however, is significant in the US HY market only, whereas excess returns are not statistically significant for beta. The information ratios range from 0.04 (beta) to 0.50 (momentum) in the US HY market and from −0.03 (beta) to 1.05 (momentum) in the US IG market. However, the single-factor tracking errors suggest that investing in factor portfolios can be risky in relative terms. Tracking errors range from 2.64 to 5.43% for US HY and 0.93 to 1.49% for US IG corporate bonds, and thus are quite large compared to the market volatilities of 9.84% and 3.80%. Due to these higher tracking errors, single-factor portfolios might not be conducive for investors looking for benchmark-oriented portfolio management. Instead, investors who consider factor investing with corporate bonds should strategically allocate to factors in order to harvest risk premia on a consistent basis (see [ANG 09]). Figures 9.1 and 9.2 show the single-factor portfolio performance versus their corresponding benchmarks.

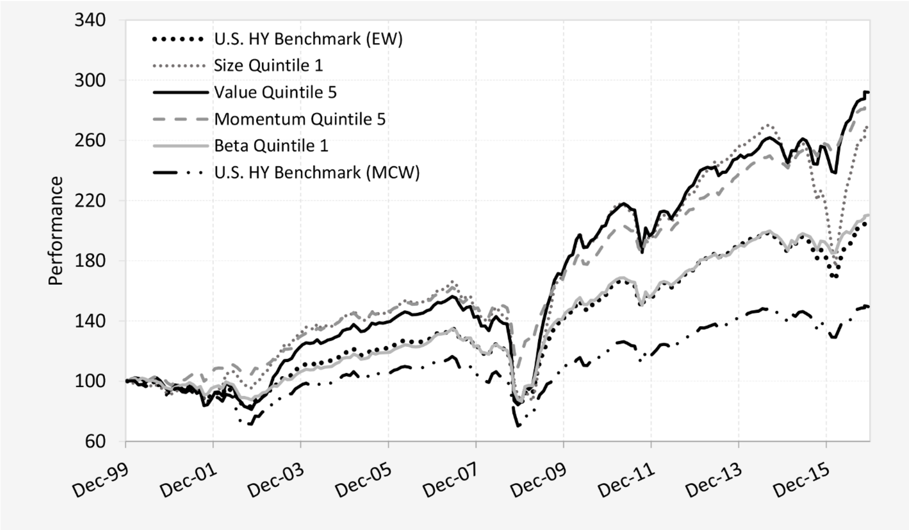

Figure 9.1. *Cumulative US HY single-factor portfolio returns (December 1999–November 2016)*

9.5.3. *Multi-factor performance*

Ever since the development of modern portfolio theory in the 1950s (see [MAR 52]), the idea of diversification survived by proposing that a portfolio constructed of different assets (here factors) will, on average, generate higher risk-adjusted returns than any individual asset found within the portfolio (only true if the assets or factors in the portfolio are not perfectly correlated). Table 9.3 shows correlations of excess returns[9] of the four factors as well as the multifactor portfolios for US HY and IG credit markets. The lowest correlations are between the HY momentum and HY size factors (−0.54) as well as between IG beta and IG size

9 Here excess return denotes return over benchmark.

(−0.47). Hence, a combination of these factors offers significant diversification benefits. In addition, all factors exhibit equal or higher SRs compared to the market. Therefore, we combine all four factors into a multifactor portfolio.

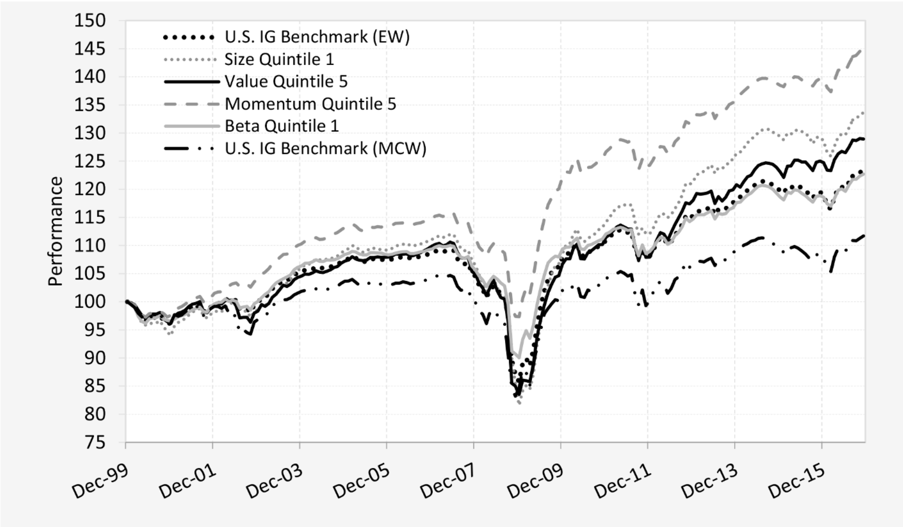

Figure 9.2. *Cumulative US IG single-factor portfolio returns (December 1999–November 2016)*

We also construct EW long-only multifactor portfolios by combining size, value, momentum and beta, as described by:

$$r_t^{MultiFactor} = 0.25r_t^{Size} + 0.25r_t^{Value} + 0.25r_t^{Momentum} + 0.25r_t^{Beta} \qquad [9.8]$$

where r_t denotes the return of each corresponding single-factor portfolio as well as the multifactor portfolio in month t.

Table 9.2 reports the multifactor portfolio statistics. The multifactor portfolio delivered an annual average excess return of 5.95% in the US HY market and 1.68% in the US IG market. Interestingly, the alphas of the multifactor portfolios remain significant in both markets after controlling for corresponding equity factor exposures, indicating that the combination of factors add value beyond the equity factors.

US high yield	Market (MCW)	Market (EW)	Multifactor
Panel (A): Top-decile risk/return			
Mean	2.40%	4.37%	5.95%
Volatility	10.42%	9.84%	10.47%
Sharpe ratio	0.23	0.44	0.57
Panel (B): Excess return vs. market (EW)			
Alpha			1.58%***
t-stat			3.73
Tracking error			1.73%
Information ratio			0.91
Panel (C): 5-Factor alpha vs. market (EW)			
Alpha			1.32%***
t-stat			3.26
US investment grade			
Panel (A): Top-decile risk/return			
Mean	0.66%	1.25%	1.68%
Volatility	4.17%	3.80%	3.82%
Sharpe ratio	0.16	0.33	0.44
Panel (B): Excess return vs. market (EW)			
Alpha			0.43%***
t-stat			3.34
Tracking error			0.52%
Information ratio			0.82
Panel (C): 5-Factor alpha vs. market (EW)			
Alpha			0.42%***
t-stat			3.32

Table 9.2. *Performance summary of multifactor portfolios. Results of multifactor portfolios compared to the MCW and EW US HY as well as the US IG corporate bond market. The multifactor portfolio consists of an EW combination of all four analyzed factors. Statistical significance is denoted by *, ** and *** corresponding to the 90, 95 and 99% confidence levels, respectively*

Moreover, the EW combination of size, value, momentum and beta within the different markets and segments generates higher SRs than the EW market index. These findings suggest that the combination of all four factors leads to diversification benefits. Over our sample period and the EW multifactor portfolios demonstrate an annualized SR of 0.57% for US HY and 0.44% for US IG corporate bonds while SRs of their corresponding markets are 0.44% and 0.33%, respectively. Figures 9.3 and 9.4 show the multifactor portfolio performance versus the benchmark as well as the cumulative outperformance.

	IG size	IG value	IG MOM	IG beta	IG MF	HY size	HY value	HY MOM	HY beta	HY MF
IG size	1.00									
IG value	0.07	1.00								
IG MOM	−0.38	−0.33	1.00							
IG beta	−0.47	0.20	0.45	1.00						
IG MF	0.32	0.70	0.16	0.48	1.00					
HY size	0.41	0.13	−0.40	−0.37	0.02	1.00				
HY value	0.04	0.59	−0.39	0.01	0.27	0.29	1.00			
HY MOM	−0.33	−0.31	0.58	0.34	−0.03	−0.54	−0.43	1.00		
HY beta	−0.01	−0.06	0.18	0.27	0.15	-0.27	−0.13	0.33	1.00	
HY MF	0.15	0.31	−0.18	0.02	0.25	0.57	0.64	−0.01	0.27	1.00

Table 9.3. *Correlation summary of single- and multi-factor portfolio outperformances. Return correlations between US HY and IG single- and multifactor portfolios (size, value, momentum (MOM), beta and multifactor (MF)) over the period December 1999–November 2016*

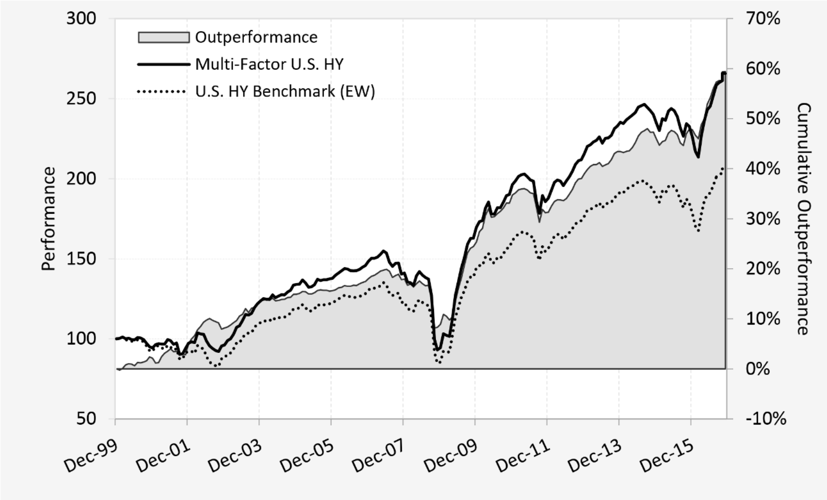

Figure 9.3. *Cumulative US HY multifactor portfolio returns (December 1999–November 2016)*

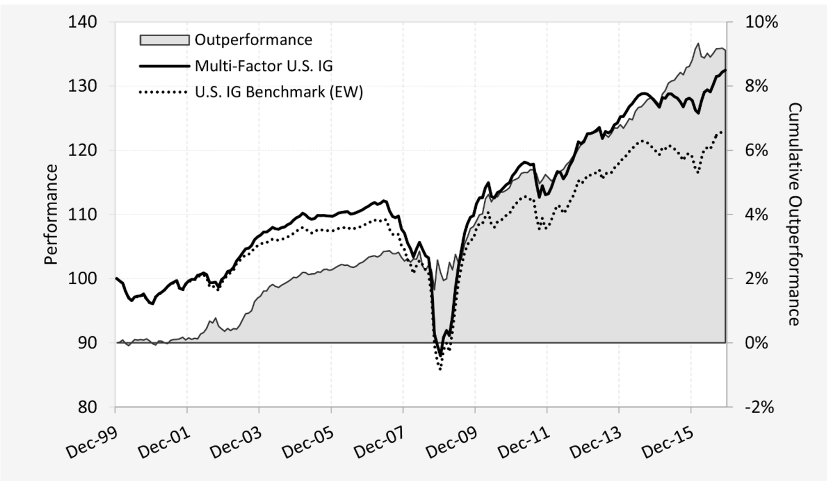

Figure 9.4. *Cumulative US IG multifactor portfolio returns (December 1999–November 2016)*

9.5.4. *Factor performance after transaction costs*

Corporate bonds are typically traded less frequently than stocks. Therefore, most academic research focuses on low turnover strategies in order to avoid high transaction costs. We follow [ISR 16] and estimate transaction costs as a function of issue rating, maturity and total turnover associated with each factor portfolio according to [CHE 07].

US high yield	Market	Size	Value	Momentum	Beta	Multifactor
Gross return	4.37%	6.01%	6.54%	6.40%	4.49%	5.95%
Transaction costs	0.31%	0.38%	0.48%	0.59%	0.42%	0.45%
Net return	4.06%	5.63%	6.06%	5.81%	4.07%	5.50%
Volatility	9.84%	13.38%	13.40%	7.89%	9.09%	10.47%
Net Sharpe ratio	0.41	0.42	0.45	0.74	0.45	0.53
US investment grade						
Gross return	1.25%	1.73%	1.51%	2.22%	1.22%	1.68%
Transaction costs	0.12%	0.14%	0.21%	0.31%	0.18%	0.21%
Net return	1.13%	1.59%	1.30%	1.91%	1.04%	1.47%
Volatility	3.80%	4.41%	4.57%	3.24%	3.52%	3.82%
Net Sharpe ratio	0.30	0.36	0.28	0.59	0.30	0.38

Table 9.4. *Performance summary of factor portfolios after transaction costs. Performance results of the market, size, value, momentum, beta and multifactor portfolios for the US HY as well as the US IG corporate bond markets after transaction costs. Transaction costs are calculated according to Chen et al. [CHE 07]. Gross returns, transaction costs, net returns, volatilities and SRs are annualized*

We document that our results remain economically feasible after accounting for transaction costs. Thus, the factors studied here are not only properly motivated and theoretically sound but can also be implemented. As our definitions are based on existing academic literature, our selection is not based on *ex post* results, thereby freeing our results of data mining biases.

9.6. Conclusion

In this analysis, we show that the classical equity factors size, value, momentum and beta, factors well-known for their robust risk premia in equity space, should be considered for corporate bond investing.

We find that investing in multifactor portfolios substantially improves performance compared to investing in market indices. Our main inference that the four analyzed factors generate positive risk-adjusted returns, especially when viewed in a multifactor context, is unaffected by the impact of transaction costs. Moreover, investing in a multifactor portfolio reduces tracking error and drawdowns while preserving higher risk-adjusted returns when compared to market indices.

Finally, our results remain robust after accounting for Fama–French equity factors size and value as well as momentum. Our results indicate that factor-based investing with corporate bonds does indeed offer value to corporate bond investors beyond equity factors. Interestingly, all factors but beta lead to economically and statistically significant results for the US HY market. We conjecture that this observation is due to the more equity-like features of HY bond markets compared to IG bond markets (see [HON 12]). As the traditional factors have shown to hold significant explanatory power for equity market returns, it is not surprising that these equity factors perform better in more equity-like bond markets (see [BEK 16]).

Since fixed-income indices can vary greatly in their risk and return profiles and are usually non-investable benchmarks, the demand for improved fixed-income indices will continue to grow especially in the context of diversification, liquidity and management costs. We hope the findings presented here will encourage academic researchers to advance research on factor-based investing in credit space and market practitioners to deploy factors in their daily asset management decisions.

9.7. Bibliography

[AME 12] AMENC N., GOLTZ F., LODH A. *et al.*, "Diversifying the diversifiers and tracking the tracking error: outperforming cap-weighted indices with limited risk of underperformance", *The Journal of Portfolio Management*, vol. 38, no. 3, p. 72–89, 2012.

[ANG 09] ANG A., GOETZMANN W., SCHAEFER S., Evaluation of active management of the Norwegian government pension fund – global, Report to the Norwegian Ministry of Finance, 2009.

[ANG 14] ANG A., *Asset Management: A Systematic Approach to Factor Investing*, Oxford University Press, New York, 2014.

[ASN 13] ASNESS C., MOSKOWITZ T., PEDERSEN L., "Value and momentum everywhere", *Journal of Finance*, vol. 68, p. 929–985, 2013.

[BAK 12] BAKER M., WURGLER J., "Comovement and predictability relationships between bonds and the cross-section of stocks", *Review of Asset Pricing Studies*, vol. 2, p. 57–87, 2012.

[BAN 81] BANZ R., "The relationship between return and market value of common stocks", *Journal of Financial Economics*, vol. 9, p. 3–18, 1981.

[BAS 77] BASU S., "Investment performance of common stocks in relation to their price-earnings ratios: a test of the efficient market hypothesis", *Journal of Finance*, vol. 32, p. 663–682, 1977.

[BEK 16] BEKTI D., WENZLER J.-S., WEGENER M. *et al.*, Extending Fama-French factors to corporate bond markets, Working paper, Darmstadt University of Technology and Deka Investment GmbH, Darmstadt, 2016.

[BEN 97] BENARTZI S., MICHAELY R., THALER R., "Do changes in dividends signal the future or the past?", *Journal of Finance*, vol. 52, p. 1007–1034, 1997.

[BHO 09] BHOJRAJ S., SWAMINATHAN B., "How does the corporate bond market value capital investments and accruals?", *Review of Accounting Studies*, vol. 14, p. 31–62, 2009.

[BLA 72] BLACK F., JENSEN M., SCHOLES M., "The capital asset pricing model: some empirical tests", in JENSEN M. (ed.) *Studies in the Theory of Capital Markets*, Praeger, New York, 1972.

[BLA 15] BLACKROCK, Smart Beta Guide, BlackRock, Canada, 2015.

[CAR 97] CARHART M., "On persistence in mutual fund performance", *Journal of Finance*, vol. 52, p. 57–82, 1997.

[CHE 07] CHEN L., LESMOND D.A., WEI J., "Corporate yield spread and bond liquidity", *Journal of Finance*, vol. 62, p. 119–149, 2007.

[EDW 07] EDWARDS A., HARRIS L., PIWOWAR M., "Corporate bond market transaction costs and transparency", *Journal of Finance*, vol. 62, p. 1–21, 2007.

[FAM 92] FAMA E., FRENCH K., "The cross-section of expected stock returns", *Journal of Finance*, vol. 47, p. 427–465, 1992.

[FAM 93] FAMA E., FRENCH K., "Common risk factors in the returns on stocks and bonds", *Journal of Financial Economics*, vol. 33, p. 3–56, 1993.

[FAM 15] FAMA E., FRENCH K., "A five-factor asset pricing model", *Journal of Financial Economics*, vol. 116, p. 1–22, 2015.

[FRA 14] FRAZZINI A., PEDERSEN L., "Betting against beta", *Journal of Financial Economics*, vol. 111, p. 1–25, 2014.

[GEB 05] GEBHARDT W., HVIDKJAER S., SWAMINATHAN B., "Stock and bond market interaction: does momentum spill over?", *Journal of Financial Economics*, vol. 75, p. 651–690, 2005.

[HAR 16] HARVEY C.R., LIU Y., ZHU H., "...and the cross-section of expected returns", *Review of Financial Studies*, vol. 29, p. 5–68, 2016.

[HAU 72] HAUGEN R., HEINS A., On the evidence supporting the existence of risk premiums in the capital market, Working paper, Wisconsin, 1972.

[HON 12] HONG Y., LIN H., WU C., "Are corporate bond market returns predicable?", *Journal of Banking and Finance*, vol. 36, p. 2216–2232, 2012.

[HOU 17] HOUWELING P., VAN ZUNDERT J., "Factor investing in the corporate bond market", *Financial Analyst Journal*, pp. 100–115, 2017.

[ISR 16] ISRAEL R., PALHARES D., RICHARDSON S., Common factors in corporate bond and bond fund returns, Working paper, AQR Capital Management, USA, 2016.

[JEG 93] JEGADEESH N., TITMAN S., "Returns to buying winners and selling losers: implications for stock market efficiency", *Journal of Finance*, vol. 48, p. 65–91, 1993.

[JOS 13] JOSTOVA G., NIKOLOVA S., PHILIPOV A. *et al.*, "Momentum in corporate bond returns", *Review of Financial Studies*, vol. 26, p. 1649–1693, 2013.

[MAR 52] MARKOWITZ H., "Portfolio selection", *Journal of Finance*, vol. 7, no. 1, p. 77–91, 1952.

[MER 74] MERTON R., "On the pricing of corporate debt: the risk structure of interest rates", *Journal of Finance*, vol. 29, p. 449–470, 1974.

[SHA 64] SHARPE W., "Capital asset prices: a theory of market equilibrium under conditions of risk", *Journal of Finance*, vol. 19, p. 425–442, 1964.

[SIE 03] SIEGEL L.B., *Benchmarks and Investment Management*, Research Foundation of CFA Institute, Charlottesville, 2003.

[STA 12] STAMBAUGH R.F., YU J., YUAN Y., "The short of it: investor sentiment and anomalies", *Journal of Financial Economics*, vol. 104, p. 288–302, 2012.

[ZHA 05] ZHANG L., "The value premium", *Journal of Finance*, vol. 60, p. 67–103, 2005.

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10

Alternative Risk Premia: What Do We Know?

The concept of alternative risk premia (ARP) is an extension of the factor investing approach. Factor investing consists of building long-only equity portfolios which are directly exposed to common risk factors such as size, value or momentum. ARP designate non-traditional risk premia other than a long exposure to equities and bonds. They may involve equities, rates, credit, currencies or commodities and correspond to long-short portfolios. However, contrary to traditional risk premia, it is more difficult to define ARP in terms of which risk premia really matter. In fact, the term "alternative risk premia" encompasses two different types of systematic risk factor: skewness risk premia and market anomalies. For example, the most frequent ARP are carry and momentum, which are, respectively, a skewness risk premium and a market anomaly. Because the returns of ARP exhibit heterogeneous patterns in terms of statistical properties, option profiles and drawdown, asset allocation is more complex than with traditional risk premia. In this context, risk diversification cannot be reduced to volatility diversification and skewness risk becomes a key component of portfolio optimization. Understanding these different concepts and how they interconnect is essential for improving multi-asset allocation.

Chapter written by Thierry RONCALLI (Amundi Asset Management).

This survey has been prepared for the book *Factor Investing* edited by Emmanuel Jurczenko. It is extensively based on my three previous co-authored articles *Facts and Fantasies About Factor Investing*. A Primer on Alternative Risk Premia and *Risk Parity Portfolios with Skewness Risk: An Application to Factor Investing and Alternative Risk Premia*. I am profoundly grateful to Emmanuel Jurczenko, Didier Maillard, Bruno Taillardat and Ban Zheng for their helpful comments.

10.1. Introduction

After the emergence of risk-based investing, factor investing has been the new hot topic in the asset management industry since the 2008 global financial crisis. Both concepts are related to the notion of diversification but take different standpoints. The goal of risk-based investing is to build a better diversified portfolio than a mean-variance optimized portfolio. The idea is that mathematical optimization and volatility minimization do not always lead to financial diversification. The aim of factor investing is to extend the universe of assets for building a diversified allocation by capturing systematic risk factors. For instance, in the equity space, the capital asset pricing model has been supplemented by a five-factor model which is based on size, value, momentum, low beta and quality risk factors.

The concept of ARP is an extension of factor investing, which is a term generally reserved for long-only equity risk factors. Indeed, ARP concern all the asset classes, not only equities but also rates, credit, currencies and commodities. Moreover, they may be implemented using long-short portfolios. To be more precise, a risk premium is compensation for taking a risk that cannot be hedged or diversified. We consider the two main traditional risk premia as corresponding to long exposures to equities and to bonds. However, since the 1980s academics have shown that there are other sources of risk premia. For instance, cat bonds must incorporate a risk premium because the investor takes a large risk that cannot be diversified. Therefore, ARP designate all the risk premia other than long exposures to equities and bonds.

Contrary to traditional risk premia, whose risk/return profile is relatively easy to understand, the behavior of ARP is more heterogeneous. In fact, the term covers two main categories of strategy: skewness risk premia and market anomalies. Skewness risk premia are “pure” risk premia, meaning that they reward systematic risks in bad times. Conversely, market anomalies are strategies that have performed well in the past but whose performance cannot be explained by the existence of a risk premium. For example, momentum and trend-following strategies are market anomalies, whereas carry strategies are generally considered as skewness risk premia. As a result, statistical properties and option profiles are different from one risk premium to another. In particular, skewness risk premia may exhibit a high skewness risk. Although portfolio allocation between traditional risk premia is usually based on expected returns and the covariance matrix, portfolio management cannot ignore the third statistical moment. This issue is particularly important because some investors see portfolios of alternative risk premia as all-weather strategies. However, this is not the case in reality.

Diversification is the primary objective when investing in ARP. The second motivation is the search for higher returns, especially in a low-rate environment. In this context, ARP are performance assets and not only diversification assets. It is therefore natural that the development of ARP impacts the hedge fund industry. First, it offers a new framework for analyzing the risk/return profile of hedge fund strategies and institutional portfolios invested in alternative assets. Second, it provides new investment products that replicate the alternative beta of hedge funds. However, the most significant influence of ARP certainly involves multi-asset management, which cannot be reduced to an allocation between stocks and bonds. Indeed, ARP constitute the other building blocks of multi-asset portfolios. This is why they participate in the convergence of traditional and alternative investments.

This chapter is organized as follows. In section 10.2, we present the rationale of ARP, in particular the difference between systematic, arbitrage and specific risk factors. The study of factor investing in the equity market also helps in understanding the motivations behind the emergence of this new framework. In section 10.3, we define more precisely the concept of ARP and make the distinction between skewness risk premia and market anomalies. We can then review the different generic strategies. In particular, carry and momentum are the two most relevant ARP across the different asset classes. Section 10.4 deals with the issue of diversification and portfolio management in the presence of skewness risk. Finally, section 10.5 offers some concluding remarks.

10.2. The rationale of ARP

In order to understand the relationship between ARP and the concept of diversification, we have to go back to the works of Markowitz [MAR 52] on this topic. In a first step, we show that diversification depends on the allocation model but also on the definition of common risk factors. In a second step, using the results on the equity asset class, we show that common risk factors are the only bets that are compatible with diversification.

10.2.1. *Difference between common risk factors and arbitrage factors*

We consider a universe of n assets. Let μ and Σ be the vector of expected returns and the covariance matrix of asset returns. We denote by $x = (x_1, \ldots, x_n)$ the vector of weights in the portfolio. For Markowitz [MAR 52], the financial problem of the investor consists in maximizing the expected excess return of his portfolio subject to a constraint on the portfolio's volatility:

$$\begin{aligned} x^\star &= \arg\max x^\top (\mu - r\mathbf{1}) \\ &\text{u.c.} \sqrt{x^\top \Sigma x} \leq \sigma^\star \end{aligned} \qquad [10.1]$$

where r is the return of the risk-free asset. Markowitz [MAR 56] showed that this nonlinear optimization problem is equivalent to a quadratic optimization problem:

$$x^\star = \arg\min \frac{1}{2} x^\top \Sigma x - \gamma x^\top (\mu - r\mathbf{1}) \qquad [10.2]$$

where γ is a parameter that controls the risk aversion of the investor. Without any constraints, the mean-variance optimized (MVO) portfolio $x^\star$ is equal to $\gamma\Sigma^{-1}(\mu - r\mathbf{1})$. More generally, in the presence of linear equality and inequality constraints, MVO portfolios are of the following form:

$$x^\star \propto f\left(\mu, \Sigma^{-1}\right) \qquad [10.3]$$

where f is a complicated function that depends on the constraints. More precisely, the solution of the Markowitz optimization problem depends on the inverse of the covariance matrix and not the covariance matrix itself. Therefore, the important quantity in portfolio optimization is the information matrix $\mathcal{I} = \Sigma^{-1}$.

In order to better understand the notion of information matrix, we consider the eigen decomposition of the covariance matrix Σ:

$$\Sigma = V \Lambda V^\top \qquad [10.4]$$

where V is the matrix of eigenvectors of Σ and Λ is the diagonal matrix, whose elements are the eigenvalues of Σ. We have:

$$\begin{aligned} \Sigma^{-1} &= \left(V\Lambda V^\top\right)^{-1} \\ &= \left(V^\top\right)^{-1} \Lambda^{-1} V^{-1} \\ &= V \Lambda^{-1} V^\top \end{aligned} \qquad [10.5]$$

because V is an orthogonal matrix. It follows that the eigenvectors of the information matrix $\mathcal{I}$ are the same as those of the covariance matrix. This is not the case for eigenvalues. Indeed, the eigenvalues of $\mathcal{I}$ are the inverse of the eigenvalues of Σ.

In Figure 10.1, we consider the one-year empirical covariance matrix of stock returns that made up the FTSE 100 index in June 2012. In the top panel, we have reported the breakdown of the corresponding eigenvalues. In the case of an equity investment universe, the first risk factor of the covariance matrix is generally interpreted as the market risk factor. The next eigenvectors correspond to the

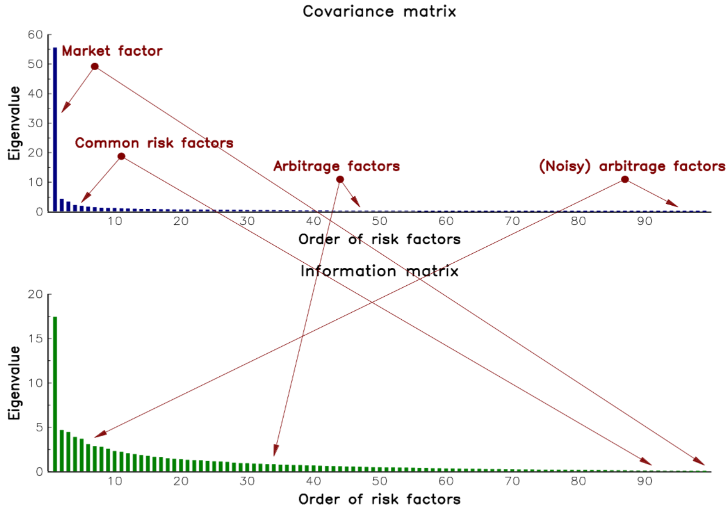


Figure 10.1. *Eigenvalues of covariance and information matrices of stock returns (FTSE 100 index, June 2012). For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

common risk factors, whereas the last eigenvectors are the arbitrage factors[1]. The breakdown of the eigenvalues of the information matrix is given in the bottom panel. In this case, the most important eigenvectors are the arbitrage factors [SCH 07]. This implies that MVO portfolios are mainly exposed to the less significant risk factors of the covariance matrix[2]. We face an issue here, because the Markowitz framework is generally presented as a diversification approach. In fact, in the case of Markowitz optimization, the common risk factors are not very interesting because they are not arbitrage factors. For instance, Markowitz optimization is not sensitive to the market risk factor. We face a paradox here because when we speak about Markowitz

1 An arbitrage factor is a long-short portfolio between a stock and the corresponding hedging portfolio of the stock. In this case, an arbitrage opportunity is detected if the long-short portfolio exhibits a significant excess return compared to the tracking error volatility of the hedging portfolio.

2 Without any constraints, the MVO portfolio is defined by:

$$x_i^\star = \gamma \sum_{j=1}^{n} \frac{v_{i,j}}{\lambda_j} \tilde{\mu}_j \qquad [10.6]$$

where λ_j is the jth eigenvalue, $v_{i,j}$ is the ith element of the jth eigenvector and:

$$\tilde{\mu}_j = \sum_{k=1}^{n} v_{k,j} \mu_k \qquad [10.7]$$

diversification, this does not mean diversification of common risk factors. Markowitz diversification means concentration on the most important arbitrage factors. Therefore, the Markowitz model is one of the most aggressive approaches in active management.

It is well known that portfolio optimization based on common risk factors requires nonlinear constraints or shrinkage. This is the case for risk budgeting (RB) portfolios. Let $\mathcal{R}(x)$ be a risk measure applied to the portfolio x. We consider a vector of risk budgets $(b_1, \ldots, b_n)$. In the RB approach, the portfolio manager chooses weights such that the risk contributions are proportional to the risk budgets:

$$\mathcal{RC}_i = x_i \cdot \frac{\partial\, \mathcal{R}(x)}{\partial\, x_i} = b_i \mathcal{R}(x) \quad [10.8]$$

If the risk budgets are the same for all the assets, the RB portfolio is called the equal risk contribution portfolio. In cases where the risk measure is the volatility, we can show that an RB portfolio is a highly regularized MVO portfolio [RON 13]. The two main differences between an RB portfolio and a traditional MVO portfolio are then the following:

1) the RB portfolio is always a long-only portfolio, whereas an MVO portfolio can be a long-short portfolio;

2) the RB portfolio is sensitive to the covariance matrix, implying it is mainly exposed to the common risk factors.

The reference to the RB portfolio is important because it is generally accepted that the RB approach is a robust way to build a diversified portfolio. Although active management (and mean-variance optimization) is associated with arbitrage factors, diversification management (and RB optimization) is related to common risk factors. A next step is then to understand what these common risk factors are. The case of factor investing in equities helps us to better assess them.

10.2.2. *Factor investing in the equity market*

Since the seminal research of Fama and French [FAM 92, FAM 93], it is accepted that the market factor defined by Sharpe [SHA 64] is not the only common risk factor that explains the cross-section variance of expected returns. Among these factors, we find the low beta factor [BLA 72], the value factor [BAS 77], the size factor [BAN 81], the momentum factor [JEG 93] and the quality factor [PIO 00]. The concept of factor investing has been popularized by Ang [ANG 14]. It consists of building (long-only) equity portfolios which are directly exposed to these common risk factors. Therefore, factor investing is a subset of smart beta or an extension of risk-based indexation. It may be curious that factor investing has become very popular since the

2008 global financial crisis, but, as we will see, this development is related to the search for diversification by long-term institutional investors [KIZ 12].

In the arbitrage pricing theory of Ross [ROS 76], the return on asset i is driven by a standard linear factor model:

$$R_i = \alpha_i + \sum_{j=1}^{n_{\mathcal{F}}} \beta_i^j \mathcal{F}_j + \varepsilon_i \quad [10.9]$$

where α_i is the intercept, β_i^j is the sensitivity of asset i to factor j and $\mathcal{F}_j$ is the (random) value of factor j. ε_i is the idiosyncratic risk of asset i, implying that $\mathbb{E}[\varepsilon_i] = 0$, $\operatorname{cov}(\varepsilon_i, \varepsilon_k) = 0$ for $i \neq k$ and $\operatorname{cov}(\varepsilon_i, \mathcal{F}_j) = 0$. The $\mathfrak{R}$-squared coefficient associated with model [10.9] is equal to:

$$\mathfrak{R}_i^2 = 1 - \frac{\sigma^2(\varepsilon_i)}{\sigma^2(R_i)} \quad [10.10]$$

It measures the part of the variance of asset returns explained by common factors. It follows that the part due to the idiosyncratic risk is equal to $1 - \mathfrak{R}_i^2$. In Table 10.1, we have reported the variance decomposition of daily returns of 6 stocks in regards to both common risk factors and the idiosyncratic risk factor. For that, we use the four-factor model of Carhart [CAR 97] based on market, size, value and momentum risk factors. For instance, if we consider the Google stock, 47% of the variance is explained by the four common risk factors and 53% by the idiosyncratic risk. If we consider the Netflix stock, 76% of the return variance corresponds to an idiosyncratic risk. At the level of individual stocks, there is a lot of alpha[3] and this alpha dominates common risk factors.

We may wonder what this result becomes if we consider diversified portfolios in place of individual stocks? In 1968, Jensen defined the alpha of a portfolio as the intercept of the linear model [10.9]. In the case of the CAPM, the alpha is then the performance of the portfolio minus the beta of the portfolio times the return of the market portfolio[4]. By applying this concept to 115 mutual funds, Jensen [JEN 68]

3 Here, the concept of alpha corresponds to the part of the return variance that is not explained by common risk factors. More generally, the alpha component is the random variable represented by the residual risk factor. In this case, the alpha can be measured as the expected return of this component (Jensen's alpha) or its variance.

4 The alpha at time t is then equal to:

$$\alpha_t = (R_t - r) - \hat{\beta}\left(R_t^{\mathrm{MKT}} - r\right) \quad [10.11]$$

where R_t is the portfolio's return, R_t^{MKT} is the return of the market portfolio, r is the return of the risk-free asset and $\hat{\beta}$ is the estimated OLS coefficient.

rejected the assumption that the alpha is positive. This implies that the active management does not produce alpha on average. Nevertheless, Hendricks *et al.* [HEN 93] noticed that this alpha is positively autocorrelated. This implies that a fund manager that has outperformed in the past has a higher probability of outperforming than underperforming in the future. This result suggested then that there is a persistence of the performance of active management and this persistence is due to the persistence of the alpha.

Stock	Common risk factors (%)	Idiosyncratic risk factor (%)
Google	47	53
Netflix	24	76
Mastercard	50	50
Nokia	32	68
Total	89	11
Airbus	56	44

Carhart's model with four factors, 2010–2014

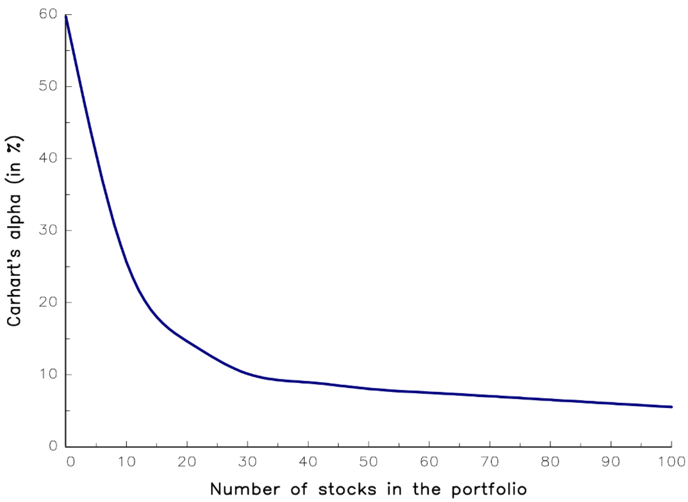
Table 10.1. *Variance decomposition of stock returns*

In 1995, Grinblatt and his co-authors [GRI 95] analyzed the quarterly portfolio holdings of 155 equity mutual funds between 1974 and 1984. They found that "77% of these mutual funds were momentum investors". Two years later, Carhart [CAR 97] proposed a four-factor model for explaining the persistence of equity mutual funds. These four factors are the market (or the traditional beta), size, value and momentum. Carhart found that the alpha calculated with the four-factor model is not autocorrelated. Carhart concluded that the persistence of the performance of active management is not due to the persistence of the alpha but in fact to the persistence of the performance of common risk factors.

Another important result concerns the relationship between diversification and risk factors. We can wonder what the optimal number of holdings of a stock picking portfolio is. It is commonly accepted that a well-diversified portfolio reduces the impact of alpha because the beta dominates the alpha if the portfolio is not concentrated in a small number of bets. This idea is shared by Warren Buffett[5], David

5 "If you can identify six wonderful businesses, that is all the diversification you need. And you will make a lot of money. And I can guarantee that going into the seventh one instead of putting more money into your first one is going to be terrible mistake. Very few people have gotten rich on their seventh best idea" [BUF 98].

Swensen[6] and other successful investors. In Figure 10.2 we have reported the proportion of Carhart's alpha (or relative active risk) with respect to the number of stocks[7]. For individual stocks, the alpha represents about 60% of the return variance. In the case of a well-diversified portfolio, the alpha is less than 10% on average.



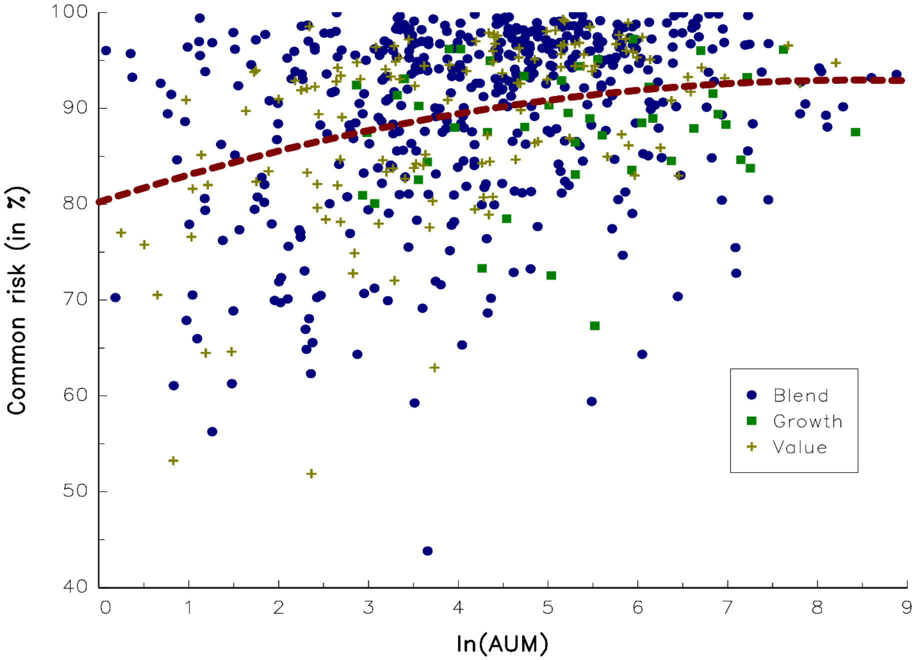
Carhart's four-factor model, equally weighted portfolio of US stocks, 2010–2014

Figure 10.2. *Proportion of Carhart's active risk with respect to the number of holdings*

We verify this rule with the Morningstar database. We consider the 880 mutual funds invested in European equities from 2010 to 2014. In Figure 10.3, we have reported the part of the performance explained by Carhart's model with respect to the logarithm of assets under management. Each symbol corresponds to one mutual fund, whereas the red dashed line corresponds to the median regression. It follows that the alpha is equal to 20% on average for small funds, whereas it is equal to 5% for large funds.

6 "Concentration is another important factor in generating high levels of incremental returns. We have managers in Yale's portfolio that will hold three or four or five stocks, or maybe eight or 10 stocks" (David Swensen, interview in [LAU 05]).

7 The asset universe corresponds to stocks that belong to the S&P 500 index. The stocks are selected randomly and the allocation is equally weighted. For a given number of stocks, we run 500 randomly generated portfolios and we calculate Carhart's alpha as 1 minus the mean of the $\mathfrak{R}$-squared coefficient obtained with the four-factor model.



Morningstar database, 880 mutual funds, European equities, 2010–2014

Figure 10.3. *Proportion of return variance explained by Carhart's four-factor model. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

It follows from the previous results that idiosyncratic risks and specific bets disappear in large and diversified portfolios. Therefore, alpha is not scalable. Common risk factors are the only bets that are compatible with diversification. This explains why long-term investors including sovereign wealth funds and pension funds are so interested in factor investing. This conclusion has been reiterated by the report on the Norwegian Government Pension Fund. Ang *et al.* [ANG 09] found that "the active management activities of the Fund account for less than one percent of the overall variance" from January 1998 to September 2009 and that "a significant part of even the very small component of the total Fund return represented by active return is linked to a number of well-recognized systematic factors".

10.3. Defining ARP

In the case of the equity asset class, we generally consider that the common risk factors are the beta, size, value, low beta, momentum and quality risk factors. The term "factor investing" is mostly used for designing long-only portfolios based on these risk factors. The concept of ARP is an extension of the concept of factor investing in the case of long-short portfolios to all asset classes, including rates, credit, currencies and commodities. It is interesting to note that some asset classes, like currencies and commodities, may exhibit ARP, but no traditional risk premia.

ARP refer to non-traditional risk premia other than long-only exposures on equities and bonds. However, ARP also refer to alternative investments and hedge fund strategies [BLI 17]. Although factor investing affects the industry of equity active management, ARP is clearly a new analytical and investment framework for multi-asset allocation and portfolios of hedge funds.

10.3.1. *Skewness risk premia and market anomalies*

Strictly speaking, a risk premium rewards an exposure to a non-diversifiable or systematic risk. For instance, the equity risk premium (ERP) is defined as the reward that investors expect for being exposed to the equity risk. Although equity and bond risk premia are the two traditional risk premia, there are others. A famous example is the premium embedded in cat bonds, which are insurance-linked securities that transfer catastrophe risks like hurricanes to investors. In this specific case, it is obvious that the risk taken by investors is non-diversifiable and non-hedgeable and must be rewarded. However, the existence of a risk premium is not always easy to justify for many strategies. Nevertheless, the consumption-based model of Lucas [LUC 78] helps to better characterize the concept of risk premia. According to Cochrane [COC 01], the risk premium associated with an asset is equal to[8]:

$$\underbrace{\mathbb{E}_t\left[R_{t+1}-R_{f,t}\right]}_{\text{Risk premium}} \propto \underbrace{-\rho\left(u'\left(C_{t+1}\right),R_{t+1}\right)}_{\text{Correlation term}} \times \underbrace{\sigma\left(u'\left(C_{t+1}\right)\right)}_{\text{Smoothing term}} \times \underbrace{\sigma\left(R_{t+1}\right)}_{\text{Volatility term}} \qquad [10.12]$$

where R_{t+1} is the one-period return of the asset, $R_{f,t}$ is the risk-free rate, C_{t+1} is the future consumption and $u\left(C\right)$ is the utility function. In bad times, investors decrease their consumption and the marginal utility is high. Therefore, investors agree to pay a high price for an asset that helps to smooth their consumption. To hedge bad times, investors can use assets with a low or negative risk premium. They will invest in assets that are positively correlated with these bad times only if their risk premium is high. This is why investors require a high-risk premium in order to buy assets that are negatively correlated with the marginal utility and are highly volatile. Therefore,

8 See also [MAR15] or [HAM 16].

in the consumption-based model, the risk premium is compensation for accepting risk in bad times [ANG 14].

The study of mean-reverting and trend-following strategies is of particular interest for understanding whether they exhibit a risk premium. In sections 10.6.1 and 10.6.2, we present a simple analytical framework in order to obtain the main properties of these two canonical strategies. We show that their probability distribution is very different (see Figure 10.4). The trend-following strategy has a positive skewness, a bounded loss and a significant probability of infinite gain [POT 06]. On the contrary, the contrarian strategy has a negative skewness, a bounded gain and a significant probability of infinite loss. The contrarian strategy can then have a risk premium but not the trend-following strategy. Moreover, the loss of the contrarian strategy generally occurs at bad times (or when the performance of traditional risk premia is very bad).

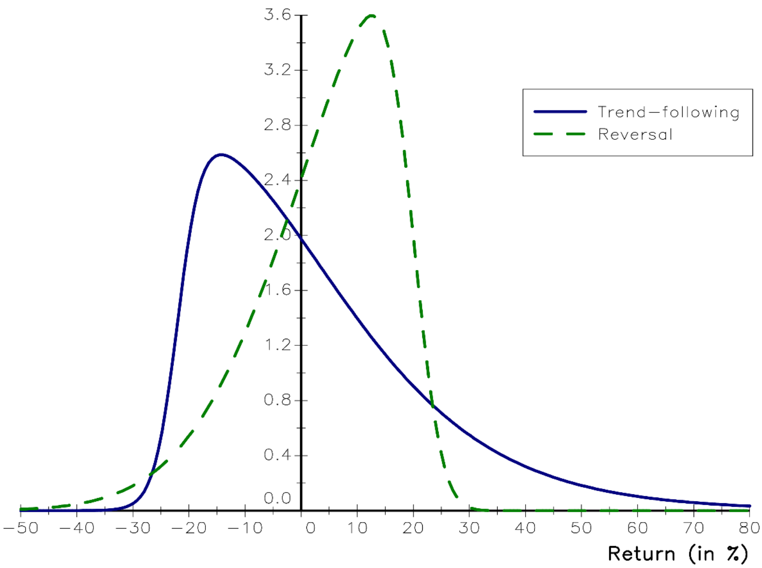


Figure 10.4. *Probability density function of contrarian and trend-following strategies. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

Let us come back to the equity factor investing framework. While size and value factors are two mean-reverting strategies, they can exhibit a risk premium [HAM 16]. This is not the case with the momentum risk factor. Concerning low beta and quality factors, there is no evidence that they reward a non-diversifiable risk during bad times. Here we have precisely the opposite situation. During a stock market crisis, these two strategies are generally more resilient and outperform a buy-and-hold strategy in a cap-weighted index. Therefore, the good past performance of momentum, low beta and quality risk factors is not due to a risk premium but is explained by the theory of behavioral finance[9]. When a strategy has performed well in the past and it is not due to the existence of a risk premium, it is called a market anomaly [HOU 15].

In practice, investors and portfolio managers consider that ARP cover two types of strategies:

1) Pure risk premia, also called skewness risk premia, correspond to the previous definition [LEM 14], for example the size and value risk factors are two skewness risk premia.

2) Market anomalies correspond to trading strategies that have delivered good performance in the past, but whose performance cannot be explained by the existence of a systematic risk at bad times. Their performance can only be explained by behavioral theories, for example the momentum, low beta and quality risk factors are three market anomalies.

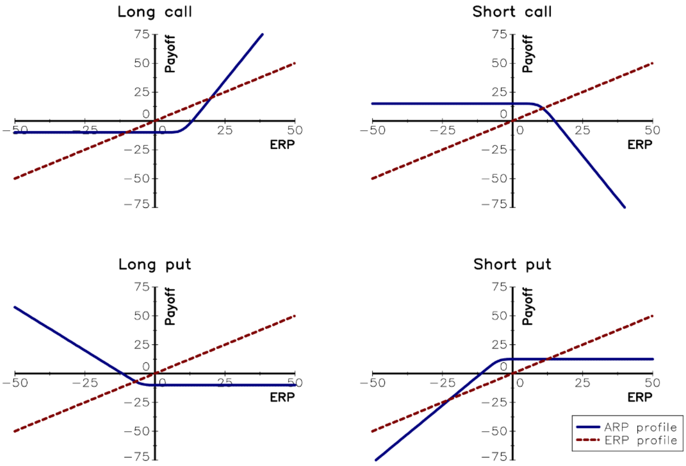


Figure 10.5. *Which option profile may exhibit a risk premium? For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

9 For instance, the momentum pattern may be explained by either an underreaction to earnings announcements and news, a delayed reaction, excessive optimism or pessimism, etc. [BAR 03]. The strong performance of low beta and low volatility assets may be explained by investors' leverage aversion [FRA 14]. The quality strategy is another good example of strong and consistent abnormal returns not related to risk [ASN 14].

In order to better understand the difference between a skewness risk premium and a market anomaly, we report the generic payoffs of trading strategies with respect to the ERP in Figure 10.5. In this case, bad times correspond to the drawdown of the stock market. If the payoff function of the trading strategy is a long call, it cannot be a risk premium because the investor is not exposed to a skewness risk. Indeed, the loss of the trading strategy is limited and small. If the payoff function of the trading strategy is a long put, again it cannot be a risk premium because the investor is rewarded in a bear market and this strategy hedges bad times. Therefore, this is an insurance premium and not a risk premium. The case of the short call profile is interesting because it exhibits a drawdown when the market is up. This means that the drawdown occurs in good times[10] and not in bad times. If this trading strategy has a positive expected return, it can only be a market anomaly, not a skewness risk premium. However, if the payoff function of the trading strategy is a short put, the investor takes a risk in bad times when the performance of the equity market is negative. In this case, this type of strategy is a skewness risk premium[11]. It is interesting to relate this analysis to the trend-following strategy for multi-asset classes[12]. Fung and Hsieh [FUN 01] showed that this strategy has a long straddle option profile[13] (Figure 10.6). Based on our analysis, it is obvious that this strategy is a market anomaly because its drawdown is not correlated to bad times.

10.3.2. *Identification of ARP*

Identifying ARP is not an easy task because there is no consensus. For instance, Harvey *et al.* [HAR 16] found more than 300 academic publications that have exhibited new risk factors and tried to explain the cross-section of expected returns. They finally concluded that "most claimed research findings in financial economics are likely false". Therefore, identifying ARP cannot be reduced to backtesting a strategy and performing a statistical analysis of past performance [COC 11]. In fact, the existence of an alternative risk premium must be backed by the existence of investment products, whose goal is indeed to harvest and replicate this risk premium. Otherwise, it would mean that the asset management industry does not believe in this risk premium. This underlying idea is the starting point of the empirical study of Hamdan *et al.* [HAM 16], who have compiled a database of 1,120 existing indices,

10 When the stock market posts a very good performance.

11 This strategy has a negative skewness. However, a strategy that exhibits a short call option payoff may also have a negative skewness. So, the value of the skewness cannot be the only criterion. Indeed, the important point is when the skewness events occur. In some sense, the concept of skewness risk premia can be related to the concept of the conditional co-skewness [ILM 12].

12 In the hedge fund industry, this strategy is known as the CTA strategy.

13 This strategy performs well when the market presents a significant (positive or negative) trend and posts negative returns in rangy or reversal markets.

which are sponsored and calculated by asset managers, banks and index providers. They have classified these products according to the mapping shown in Table 10.2.

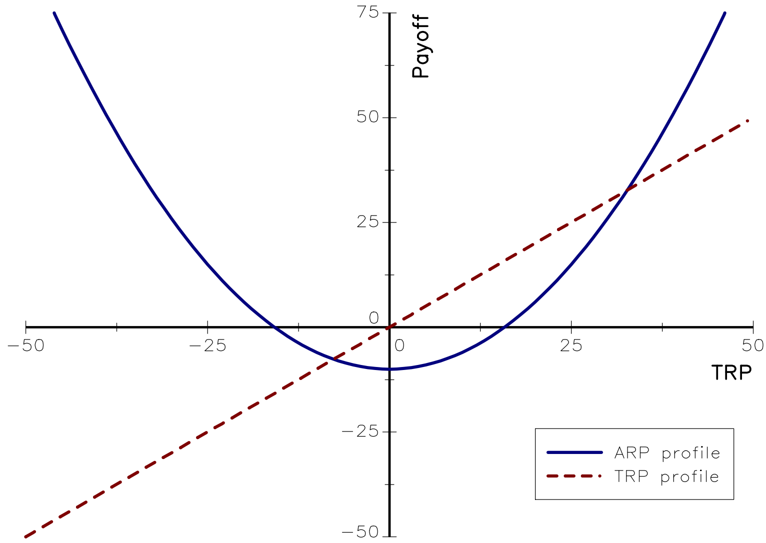


Figure 10.6. *The case of a long straddle profile. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

The different categories of risk premia are the following: carry, event, growth, liquidity, low beta, momentum, quality, reversal, size, value and volatility. This list is certainly non-exhaustive according to academic research. However, the asset management industry has either not developed products based on the other categories, or only developed them to a lesser extent, meaning that they are marginal from an investment point of view. Moreover, we notice that some categories of risk premia are not present in all asset classes. For instance, the event, growth, low beta, quality and size categories only concern the equity market. We also notice that some risk premia can be implemented in several ways and correspond to different strategies. For instance, the equity carry risk premium corresponds to the high dividend yield strategy and the dividend futures strategy. The first strategy consists of building a portfolio that is long on stocks with high dividend yields and short on stocks with low dividend yields. The aim of the second strategy consists of capturing the difference between implied and realized dividends.

Strategy	Equities	Rates	Credit	Currencies	Commodities
Carry	High dividend yield Dividend futures	Forward rate bias Term structure slope Cross-term structure	Forward rate bias	Forward rate bias	Forward rate bias Term structure slope Cross-term structure
Event	Buyback Merger arbitrage				
Growth	Growth				
Liquidity	Amihud liquidity	Turn-of-the-month	Turn-of-the-month		Turn-of-the-month
Low beta	Low beta Low volatility				
Momentum	Cross-section Time series	Cross-section Time series	Time series	Cross-section Time series	Cross-section Time series
Quality	Quality				
Reversal	Time series Variance	Time series		Time-series	Time series
Size	Size				
Value	Value	Value	Value	PPP Economic model	Value
Volatility	Carry Term structure	Carry		Carry	Carry

Table 10.2. *Mapping of alternative risk premia*

Let us briefly define the different categories[14]. The underlying idea of a carry strategy is to capture a spread or a return by betting that the underlying risk will not occur or that market conditions will stay the same [KOI 17, BAL 17]. One famous example of such a strategy is the currency carry trade. It consists of being long on currencies with high interest rates and short on currencies with low interest rates. If exchange rates do not change, this portfolio generates a positive return. In the case of bonds and commodities, we generally distinguish between several forms of carry strategies, depending on whether the carry is calculated using one maturity of the term structure (forward rate bias), two maturities of the same term structure (term structure slope) or one maturity of two different term structures (cross-yield curve).

The event category covers several idiosyncratic risk strategies, such as merger arbitrage, convertible arbitrage and buyback strategy. The growth strategy consists of selecting stocks of companies that are growing substantially faster than others. Contrary to popular belief, this is not the same as the anti-value strategy.

In the liquidity category, we find strategies whose goal is to capture the illiquidity premium of some assets [PAS 03]. In the equity asset class, the most popular illiquidity measure is the Amihud ratio [AMI 02]. In the other asset classes, liquidity strategies consist of market timing strategies and generally exploit the turn-of-the-month effect. Indeed, some (passive) investors have to roll futures contracts at some predefined periods, resulting in liquidity pressures around these rolling periods. The low beta anomaly consists of building a portfolio with exposure to low volatility stocks.

Two strategies define the momentum risk premium: cross-section momentum [JEG 93] and time-series momentum [MOS 12]. The two strategies assume that the past trend is a predictor of the future trend. The cross-section momentum strategy consists of building a portfolio that is long on assets that have outperformed and short on assets that have underperformed. In the case of the time-series momentum strategy, the portfolio is long on assets with a positive past trend and short on assets with a negative past trend[15].

The quality factor is a market anomaly that cannot be explained by a risk premium. It has been exhibited by Piotroski [PIO 00] and the strategy corresponds to a portfolio long on quality stocks and short on junk stocks without any reference to market prices [ASN 14]. Typical quality measures include equity-to-debt, return-on-equity or income-to-sales financial ratios.

14 See Hamdan *et al.* [HAM 16] for a detailed explanation of each category of risk premia and the related strategies.

15 Although cross-section momentum is related to relative returns, time-series momentum considers absolute returns.

The reversal strategy is also known as the contrarian or the mean-reverting strategy. In some sense, it is the opposite of the trend-following strategy. For an asset class, the two strategies can coexist because they do not involve the same time frequency. For instance, in the case of equities it is widely recognized that the market is contrarian in the short term (less than 1 month), trend-following in the medium term (between 1 month and 2 years) and mean-reverting in the long run (greater than 2 years). When we speak about the reversal premium, we generally consider the short-term contrarian strategy, whereas the long-term mean-reverting strategy is classified with the value risk premium. Like many ARP, there are several ways to implement such a strategy. For example, it can use short-term trends (time-series reversal) or variance differences of returns between two time horizons (variance reversal).

The underlying idea of the size factor is that small stocks have a natural excess return with respect to large stocks. This excess return may be explained by a liquidity premium or because this market is less efficient than a market of large caps. In the asset management industry, this factor is only implemented in the equity asset class.

The value equity factor was popularized by Fama and French [FAM 93, FAM 98]. This strategy goes long on undervaluated stocks and short on overvaluated stocks. Although Fama and French use the price-to-book value ratio as the value measure, asset managers generally combine different financial ratios (earnings yield, dividend yield, etc.). Choosing the approach to implement the value factor is crucial because it impacts the nature of the captured risk premium. Some products focus on the short-term value premium, whereas the majority of products try to capture the long-term value premium or the fundamental component of the value premium. In the other asset classes, the value strategy corresponds more to a long-term contrarian strategy. There are generally two main approaches for defining the long-run fundamental price. The first approach uses economic models, whereas the second approach consists of estimating the long-run equilibrium price using statistical methods.

The last risk premium concerns the volatility asset class. The volatility carry risk premium corresponds to a portfolio that captures the spread between implied volatility and realized volatility. It is also known as the short volatility strategy. Another strategy concerns the term structure of VIX futures contracts and aims to capture the roll-down effect of the slope of the term structure.

In Table 10.2, we notice that some risk premia are not present in all asset classes because they are not implemented in the industry of financial indices[16]. This mapping was valid at the end of December 2015. It does not mean that it will continue to be

16 Of course, they can be implemented in other forms by the asset management industry. For example, the event factor on fixed-income instruments is implemented by some hedge funds. The fact that there is no index means that it is more a “discretionary” strategy than a risk premium. In this case, the skill of the fund manager is essential to deliver good performance.

valid in the coming years. For example, there have been some recent attempts by asset managers to apply the quality factor to the fixed-income universe. Another identification issue is the robustness of a given category. If a category contains very few products, we can consider that the risk premium is anecdotal. For example, Hamdan *et al.* [HAM 06] only found three momentum risk premium indices on the US credit asset class. In this case, we may wonder if this risk premium really exists.

For a risk premium to be robust, there must be a sufficient number of products but they also must be sufficiently homogenous in order to represent the same common risk factor. Let us consider the case of the traditional ERP in the US market. The investor has the choice between different indices to harvest this risk premium. Selecting the index is a minor problem because the correlation between the different indices is very high[17]. This is not the case with ARP. Suppose that we have a category with five indices and that the cross-correlation between them is lower than 50%. In this case, we can believe that this category is more representative of a strategy than a risk premium. Indeed, the performance will be explained more by the portfolio construction than the intrinsic return of the common risk factor. In order to obtain a homogeneous category, Hamdan *et al.* [HAM 16] proposed a selection procedure in order to estimate the generic performance of the risk premium. They found that some categories are so heterogeneous that it is not possible to obtain a subset of indices that present the same patterns. This is the case with the following strategies: the carry risk premium based on dividend futures, the liquidity premium in equities, rates and currencies, the value risk premium in rates and commodities, the reversal risk premium based on the variance approach and risk premia in the credit market.

10.3.3. *Carry and momentum everywhere*

According to Hamdan *et al.* [HAM 16], the most important[18] risk premia in equities are the value risk factor, followed by the carry based on the high dividend yield approach, the low volatility, the short volatility and the momentum risk factor. In the case of currencies and commodities, the two important risk premia are the carry and momentum strategies. For the fixed-income asset class, these same risk premia are important, in addition to the short volatility strategy.

We notice that carry and momentum are the most relevant ARP. We find them in the four asset classes even if they are differently implemented. This is particularly true for the carry risk premium. It corresponds to strategies based on the term structure

17 For example, the cross-correlation between the daily returns of the S&P 500, FTSE USA, MSCI USA, Russell 1000 and Russell 3000 indices was greater than 99.5% between 2000 and 2015.

18 The importance is measured in terms of the number of homogenous indices within the category.

for rates and commodities and income strategies for equities and currencies. It also encompasses the famous short volatility strategy. For the momentum risk premium, both cross-section and time-series strategies are appropriate.

The title of this section refers to the article by Asness *et al.* [ASN 13] entitled "Value and Momentum Everywhere", that found "significant return premia to value and momentum in every asset class. The difference comes from the fact that the approach of Asness *et al.* [ASN 13] is based on backtesting, whereas the approach of Hamdan *et al.* [HAM 16] is based on the existence of current investment indices. It is interesting to notice that the asset management industry believes more in carry than in value, except for the equity asset class. This result may change in the future. For example, some recent research also exhibits a value pattern in the universe of corporate bonds [BEK 17, HOU 17, ISR 16]. However, it is unlikely that the value risk premium enjoys the same status as carry and momentum in the case of commodities and currencies. The issue comes from the mean-reverting frequency of the value strategy. When the frequency is very low (e.g. 5 years), it is extremely difficult for the asset management industry to propose investment vehicles with such a long-term horizon, but investors can always implement such a strategy at their own level. In the case of equities, two value strategies exist with two different mean-reverting frequencies[19]. The success of the value strategy in the equity space comes from the mixing of these two time horizons, which are shorter than the value frequency observed in the other asset classes.

It is especially interesting to analyze all the assets with respect to these three dimensions: carry, momentum and value (see Figure 10.7). As seen previously, the three dimensions can be reduced to two dimensions when we consider currencies and commodities. In the case of stocks, three dimensions are not sufficient and we have to include quality, size and volatility. The case of bonds is less obvious. If we consider the results of Hamdan *et al.* [HAM 16], they only have two dimensions. However, as explained before, new results reopen the debate, especially with the emergence of factor investing in the fixed-income asset class.

Although equity factor investing had a big impact on active management, ARP questions the place of hedge funds in a strategic asset allocation. Investment in hedge funds has been generally motivated by their diversification properties and ability to generate alpha with respect to a stock-bond allocation. The goal of ARP is the same. They are the primary assets of the diversification and they claim to be the new sources of performance. In fact, hedge funds and ARP are two sides of the same coin. It is no

19 A short-term strategy with a 1-month frequency and a long-term strategy whose frequency is more than 2 years. For instance, Bourguignon and de Jong [BOU 06] broke down the performance of the value strategy into a transitory time component and a structural time component. They showed that a large part of the performance is explained by the short-term component.

coincidence that most ARP are also hedge fund strategies. Moreover, an analysis of hedge funds shows that a part of their performance is explained by ARP [MAE 16]. The results of Hamdan *et al.* [HAM 16] find that equity beta, carry and momentum are the three main factors of hedge fund returns. The carry factor takes different forms: it can be a long credit position (traditional carry), carry risk premia in rates, currencies and commodities, but also a short volatility exposure. Carry is also particularly present in relative value and event-driven hedge fund strategies. The momentum factor is the other important pillar of hedge fund strategies, particularly for CTA and managed futures strategies. In this context, ARP will have a significant impact on the hedge fund sector, but the impact will certainly be more significant on the multi-asset management industry and the design of diversified portfolios.

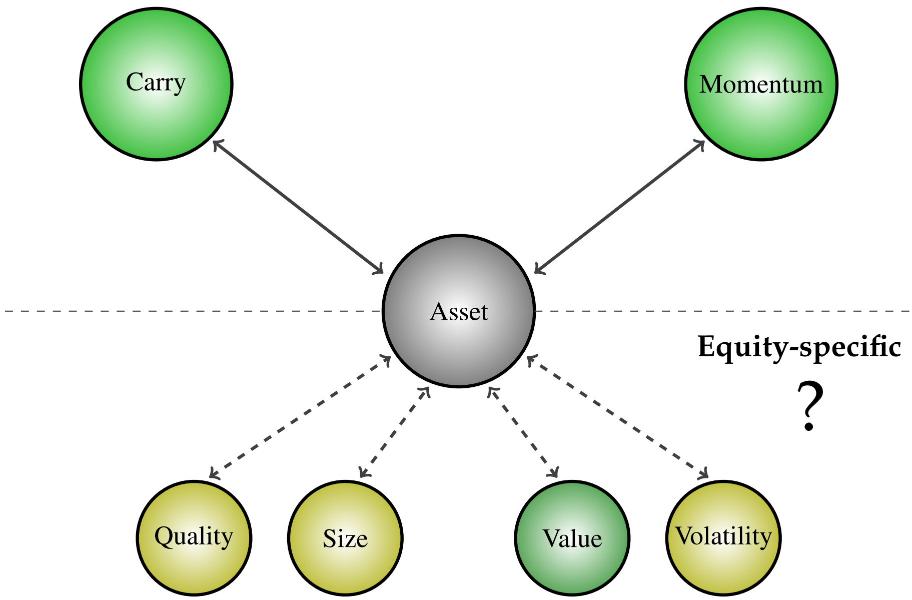


Figure 10.7. *Risk premium analysis of an asset. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

10.4. Portfolio allocation with ARP

Using a universe of ARP makes the asset allocation policy more difficult than using traditional risk premia. First, ARP are generally long-short strategies. It may be difficult to understand the behavior of some ARP with respect to a traditional long exposure on equities or bonds. Second, the skewness risk cannot be ignored and must be managed.

10.4.1. *Volatility diversification*

Let X_1 and X_2 be two random variables. The volatility of the sum is less than the sum of individual volatilities:

$$\sigma(X_1 + X_2) \leq \sigma(X_1) + \sigma(X_2) \qquad [10.13]$$

We deduce that volatility is a convex risk measure, implying that the volatility risk can be diversified. This is one of the main objectives of stock-bond asset mix policies. However, when considering a universe of equity and bond capitalization-weighted (CW) indices for different regions, we observe a limitation to the volatility diversification. Indeed, the marginal diversification becomes very quickly close to zero. The problem comes from the fact that the asset correlation is very high within the set of equity CW indices or the set of bond CW indices. In Figure 10.8, we report the breakdown of eigenvalues of a covariance matrix calculated with 17 traditional risk premia[20]. We notice that the two principal components explain about 75% of the total variance of the investment universe. If we now consider the universe of ARP, we observe that there is more volatility diversification. Indeed, the two principal components explain about 50% of the total variance of the investment universe. Five principal components are sufficient to explain more than 90% of the total variance of the TRP universe. In the case of the ARP universe, we need more than 20 principal components.

The reason for this impressive volatility diversification comes from the fact that the average correlation between ARP is very low and close to 10%. For traditional risk premia, the average correlation is higher and about 50%. This difference in correlation has a big impact on diversified portfolios. Although the volatility of a diversified equity-bond portfolio is between 6% and 9%, the volatility of a well-diversified ARP portfolio may easily be below[21] 2%. However, even if the volatility risk of an ARP portfolio is low, it does not mean that the drawdown risk is low.

10.4.2. *Skewness aggregation*

The skewness of a random variable X is defined as:

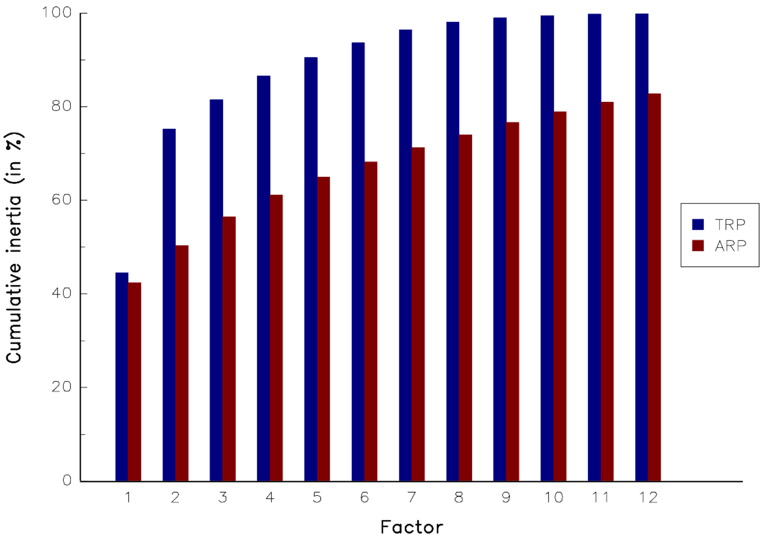
$$\gamma_1(X) = \frac{\mu_3(X)}{\mu_2(X)^{3/2}} \qquad [10.14]$$

20 The set is composed of eight equity indices, seven bond indices, two currency indices and one commodity index.

21 This explains why ARP investment products are generally leveraged in order to obtain a higher volatility.

where $\mu_n(X)$ is the $n\text{th}$ central moment of X. Contrary to the volatility, the skewness is not a convex risk measure, meaning that[22]:

$$|\gamma_1(X_1 + X_2)| \gtreqless |\gamma_1(X_1) + \gamma_1(X_2)| \qquad [10.15]$$



Source: Hamdan *et al.* [HAM 16]

Figure 10.8. *Principal component analysis of TRP and ARP investment universes. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

Therefore, the skewness of the sum may be lower or greater than the sum of individual skewness coefficients. We illustrate this property in Figure 10.9. For that, we assume that the opposite of the random vector $X = (X_1, X_2)$ follows a bivariate log-normal distribution:

$$-\begin{pmatrix} X_1 \\ X_2 \end{pmatrix} \sim \mathcal{LN}\left(\begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}, \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix}\right) \qquad [10.16]$$

For different sets of parameters, we report the relationship between the correlation parameter ρ of the log-normal distribution and the aggregated skewness coefficient $\gamma_1(X_1 + X_2)$. We notice that the highest skewness (in absolute value) is always reached when the parameter ρ is equal to -1 or when the aggregated volatility is

22 We use the absolute value because the skewness can be either positive or negative.

minimum. This means that the diversification of the second moment is faster than the diversification of the third moment. In the case of the fourth panel in Figure 10.9, we notice that $\gamma_1 (X_1 + X_2) \in [-2.91, -0.31]$, whereas the individual skewness is equal to -0.6. The skewness risk of a portfolio can therefore be larger than the skewness risk of the assets that belong to the portfolio.

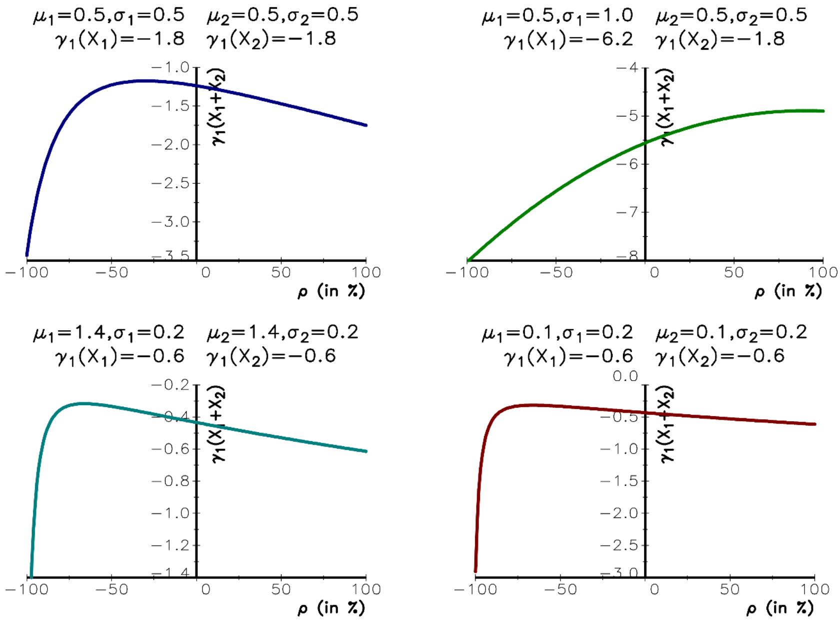


Figure 10.9. *Illustration of skewness aggregation with the bivariate log-normal distribution. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

These examples show that there is maximum diversification if we consider the skewness risk measure. The problem is twofold. First, volatility diversification is a limiting factor for skewness diversification. Indeed, by decreasing the volatility, we implicitly increase the skewness coefficient, all other things being equal. Second, the diversification of the third moment is an issue too, in that it is extremely difficult to hedge large losses. How can we explain this discrepancy between the behavior of the second moment and the behavior of the third moment? The answer lies in understanding the stochastic dependence between skewness risk premia. When a stochastic process exhibits high skewness, we generally break it down into a trend component, a Brownian component and a singular component. Unlike regular and irregular variations that are easy to diversify, it is difficult to hedge discontinuous variations. In their simplest form, these singular variations are jumps. The worst-case scenario concerning skewness aggregation is thus to build a well-diversified portfolio by dramatically reducing the volatility of the portfolio. Indeed, it is extremely difficult to diversify the negative jump of an asset. For that, we need to find a second asset that jumps at the same time and has a positive jump. Moreover, bad times for skewness risk premia tend to occur at the same time. By accumulating ARP, we then increase the volatility diversification and reduce the absolute value of the drawdown, but the drawdown of the portfolio compared to its realized volatility appears to be very high. This explains that the Sharpe ratio is not the right measure for evaluating the risk/return ratio of an ARP portfolio.

10.4.3. *Portfolio management*

In order to establish clear rules about asset allocation, we have to understand the significance of the skewness risk[23]. In the top panel in Figure 10.10, we report the cumulative performance of US equities[24] and the US volatility carry premium[25]. If we consider weekly returns, it appears that the skewness of the US volatility carry premium is 13 times the skewness of US equities. This high skewness risk is explained by the magnitude of historical drawdowns with respect to the historical volatility. Indeed, we notice that the short volatility strategy experienced very low volatility most of times, implying that this risk premium seems to have a very low risk during long historical periods. However, in a period of stress, the short volatility strategy may suffer greatly and its drawdowns appear very large compared to the observed volatility. Moreover, the drawdowns occur suddenly and correspond to negative jumps. In the case of equities, the drawdowns are also very large in absolute value, but they are relatively in line with the volatility of the stock market. Moreover, the drawdowns are generally accompanied by an increase in volatility, implying that generating said drawdowns is a more gradual process. Therefore, the skewness risk corresponds to a drawdown risk produced by a sudden jump. The short volatility strategy is emblematic of the skewness risk as it is certainly the most skewed alternative risk premium.

In section 10.6.4, we consider a classic jump-diffusion process for modeling asset returns. It follows that the associated density function can be approximated by a Gaussian mixture model with two regimes:

– a normal regime, whose returns are driven by a multivariate Gaussian distribution;

– a jump regime, whose returns are driven by another multivariate Gaussian distribution.

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23 See Jurczenko and Maillet [JUR 06] for a review of the literature on portfolio management with skewness.

24 It is approximated by the S&P 500 index.

25 We use the generic performance of the US short volatility strategy obtained by Hamdan *et al.* [HAM 16].

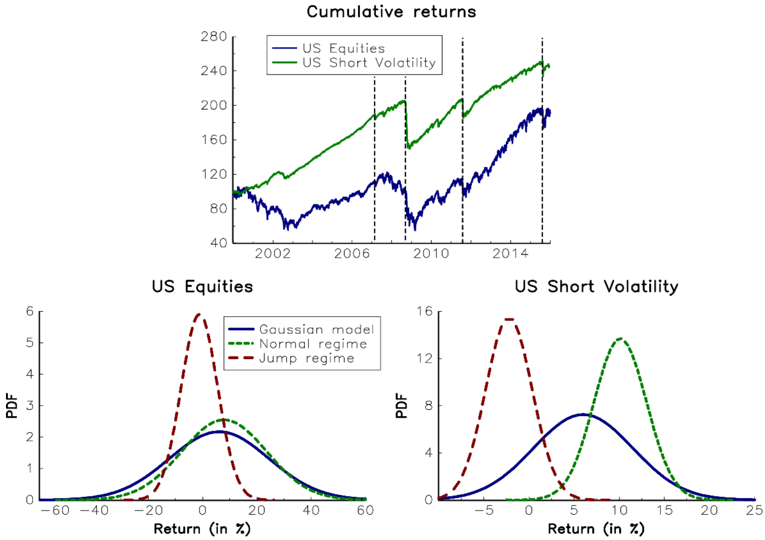

Figure 10.10. *Skewness risk of US equities and US short volatility premium. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

By construction, the occurrence probability of the jump regime is very low compared to the normal regime. This framework, which has been developed by Bruder *et al.* [BRU 16], is very appealing because it reproduces many stylized facts concerning ARP. In Figure 10.11, we have reported the Sharpe ratio, the volatility and the skewness of a portfolio invested in n ARP strategies[26], whose density function of returns is given by equation [10.34] . We notice that the Sharpe ratio increases dramatically with the number of ARP in the portfolio. This is due to the volatility diversification. However, we also notice that the skewness risk increases, even if the third moment decreases in absolute value. Therefore, a short-sighted investor feels that the risk decreases by accumulating skewness risk premia because the volatility goes to zero. However, the relative drawdown[27] becomes higher. As this drawdown appears suddenly at a very low frequency, the short-sighted investor believes that its

26 We assume that the ARP strategies have the same characteristics: $\mu_i = 7\%$, $\sigma_i = 4\%$, $\tilde{\mu}_i = -3\%$ and $\tilde{\sigma}_i = 4\%$. The parameter λ is equal to 25% meaning that we observe a jump every 4 years on average. The correlation between two ARP strategies is uniform and we have $\rho_{i,j} = 10\%$ for the normal regime and $\rho_{i,j} = 50\%$ for the jump regime.

27 The drawdown measured in absolute value decreases as shown by the behavior of the third moment. The relative drawdown is computed as the ratio between the absolute drawdown and the volatility. It is less than 2.5 for traditional risk premia. For some alternative risk premia, it may be equal to 5.

portfolio has low risk until the occurrence of the drawdown. It follows that the Sharpe ratio is not a good risk-return measure when considering ARP. In fact, the volatility risk is not a big concern. Investors are more focused on the absolute performance and the expected drawdown of such strategies.

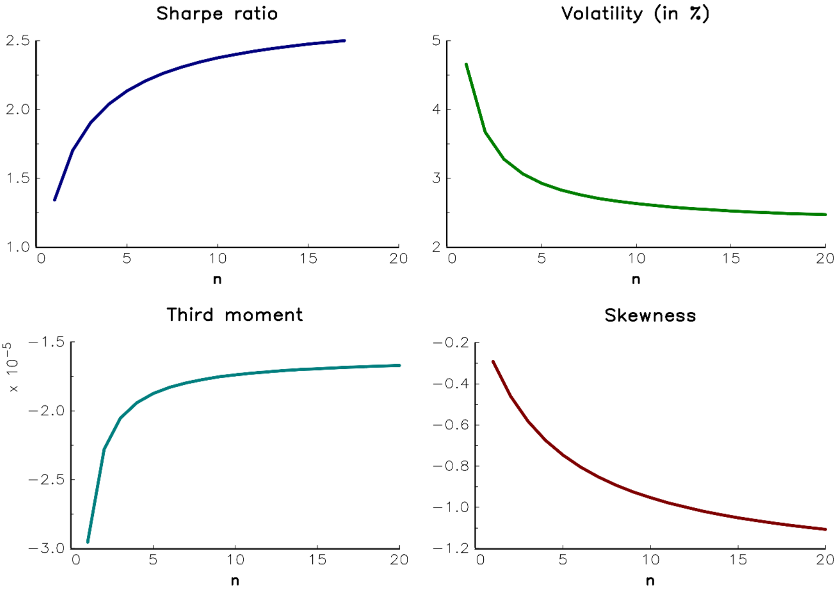

Figure 10.11. *Risk of the portfolio with respect to the number of assets. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

By applying the Gaussian mixture model to weekly returns, we obtained the probability density functions given in Figure 10.10. Here, the frequency parameter λ is equal to 26%, meaning that we observe a jump every 4 years on average[28]. We notice that the density function of the normal regime in the Gaussian mixture is relatively close to the density function of the traditional Gaussian model in the case of US equities. The volatility is then an acceptable risk measure for such assets. In the case of the short volatility strategy, we obtain another story. The jump regime has a big impact on the behavior of this risk premium. In the normal regime, the volatility carry strategy has a Sharpe ratio of about 3. However, this strong risk-return ratio is

28 In the case of the traditional Gaussian model, the estimated parameters are $\mu = 6.09\%$ and $\sigma = 18.38\%$ for US equities and $\mu = 6.00\%$ and $\sigma = 5.50\%$ for the US short volatility. In the case of the Gaussian mixture model, the estimated parameters are $\mu = 7.89\%$, $\sigma = 15.64\%$, $\tilde{\mu} = -1.20\%$ and $\tilde{\sigma} = 6.76\%$ for US equities and $\mu = 10.10\%$, $\sigma = 2.91\%$, $\tilde{\mu} = -2.23\%$ and $\tilde{\sigma} = 2.57\%$ for the US short volatility.

offset by a high jump risk, which cannot be modeled by the normal regime. This is the story of most investors between 2003 and 2007, who underestimated the risk of such a strategy.

We have seen previously that RB is the right approach for building a diversified portfolio and ARP are the common risk factors for diversifying a strategic asset allocation. Therefore, professionals have naturally combined the two approaches in order to provide well-diversified multi-asset portfolios. Generally, the construction of the portfolio is a two-stage process. First, the manager selects the best ARP. Second, the portfolio is rebalanced at a fixed frequency by defining volatility risk budgets. However, we have seen that the volatility is certainly not relevant to assess the risk of skewness risk premia because we cannot manage their bad times with a traditional risk parity method[29]. Moreover, the occurrence of a drawdown of a given skewness risk premium is followed by an increase in the realized volatility, implying that the risk parity portfolio reduces dramatically the allocation to this strategy. However, it is generally too late. If we consider again the short volatility strategy, we notice that the strategy rebounds sharply after a drawdown. Therefore, the optimal investment decision is not to reduce but to maintain or increase the exposure.

Bruder *et al.* [BRU 16] propose that the volatility risk measure of the RB method be replaced by the expected shortfall[30] based on the Gaussian mixture model. Their approach has the advantage of taking into account the skewness risk and eliminating the jumps in the allocation. This allocation is then more stable because the risk measure integrates *ex ante* the jump risk, meaning that the dynamic of the allocation is mainly driven by the true volatility and not by jumps. This point is very important, because we understand that the nature of the skewness risk is different than the nature of the volatility risk in terms of allocation dynamics. The skewness risk is a strategic asset allocation decision, implying that the investor must allocate a skewness risk budget for each risk premium in the long run and stick to this allocation even if a drawdown occurs. The volatility risk is a tactical asset allocation decision, implying that the investor may dynamically change the allocation by considering the true volatility of risk premia. Therefore, the challenge is to separate volatility and skewness effects. For instance, the empirical volatility is a biased estimator of the true volatility because it incorporates jumps. This is why we have to adopt filtering approaches for estimating the volatility of ARP.

The approach of Bruder *et al.* [BRU 16] can be simplified as follows. Suppose that we would like to allocate the risk budgets $b_1, \ldots, b_n$ to a universe of n risk premia. The idea is to transform these risk budgets that incorporate the skewness risk into new risk budgets $b'_1, \ldots, b'_n$ that are only based on the volatility risk. We can then manage the

29 By traditional risk parity, we mean an equal risk contribution portfolio based on the volatility risk measure.

30 See also [JUR 15] and [RON 15] for risk budgeting methods based on the expected shortfall.

portfolio by using a traditional RB approach and a filtered covariance matrix which do not take into account skewness events. This simplified approach shows that skewness risk premia and market anomalies do not have the same status. For instance, if we wanted to allocate the same risk budget to a skewness risk premium and a market anomaly, this would imply that the volatility budget will be higher for the market anomaly.

10.5. Conclusion

ARP cover two types of strategy: skewness risk premia and market anomalies. Skewness risk premia reward systematic risks taken by investors in bad times. An example is the short volatility strategy and, more generally, carry strategies. Market anomalies correspond to trading strategies that have delivered good performance in the past and whose performance can be explained by behavioral theories, but not by a skewness risk. For instance, momentum is a market anomaly.

Diversification covers two main risks: volatility risk and skewness risk. It is very important to understand that volatility diversification is very different to skewness diversification. In particular, managing the skewness risk is a strategic asset allocation decision, whereas managing the volatility risk is a tactical asset allocation decision. Moreover, we notice that it is extremely difficult to hedge the skewness risk because there is a floor to skewness diversification.

ARP and diversification are highly related. Until recently, multi-asset allocation was reduced to stock bond and country allocation. ARP are now an extension to the traditional risk premia universe. Investors have then a large choice of building blocks or primary assets. Of course, this new approach challenges the place of hedge funds in a strategic asset allocation. Moreover, it participates in the debate about alpha versus beta but also in the debate about passive management versus active management. Every day, the importance of alpha is decreasing alarmingly, implying that the portfolio performance is mainly explained by systematic risk factors and not by specific risk factors. The emergence of ARP renews risk/return and benchmarking analysis. However, it does not mean that active management plays a less important role in this context. Although it is more efficient to capture traditional betas using passive management, it is not straightforward to presume that it is the same thing for alternative betas. Let us take the case of carry and momentum risk premia. Even if these two premia are theoretically well defined, there are many ways for implementing them. We can harvest them using an index that encapsulates a fully detailed systematic strategy or using a portfolio manager that considers a more sophisticated quantitative model, which can be adapted to the investment and liquidity environment[31]. Certainly, these two approaches will coexist, meaning that the shift of active management from alpha toward ARP has just begun.

This chapter is dedicated to ARP based on traditional financial assets (equities, rates, credit, currencies and commodities). Another important question concerns the place of risk premia on ‘alternative’ assets (real estate, private debt, private equity, infrastructure) in a strategic asset allocation. By construction, the asset allocation policy between these risk premia cannot be driven by volatility diversification. Therefore, skewness[32] diversification remains the main issue when managing a portfolio of real assets.

10.6. Appendix: Mathematical results

10.6.1. *The contrarian (or reversal) strategy with a price target*

Let S_t be the price of an asset. We assume that S_t follows a geometric Brownian motion:

$$\mathrm{d}S_t = \mu_t S_t \,\mathrm{d}t + \sigma_t S_t \,\mathrm{d}W_t \tag{10.17}$$

The reversal strategy is described by the number of assets $f(S_t)$ held at time t:

$$f(S_t) = m\frac{\left(\bar{S} - S_t\right)}{S_t}, \tag{10.18}$$

where $\bar{S}$ is the price target of the asset and $m > 0$. If the current price is lower than the target level ($S_t \leq \bar{S}$), the nominal exposure $f(S_t)\, S_t$ is positive. On the contrary, we obtain a short exposure if the current price is higher than the target level. Hamdan *et al.* [HAM 16] show that:

$$X_T - X_0 = m\bar{S}\ln\frac{S_T}{S_0} - m\left(S_T - S_0\right) + \frac{m}{2}\bar{S}\int_0^T \sigma_t^2 \,\mathrm{d}t \tag{10.19}$$

We obtain a concave payoff with positive vega. Therefore, the strategy benefits from the volatility risk. Hamdan *et al.* [HAM 16] also demonstrated that the skewness of this strategy is always negative.

31 Moreover, the allocation between alternative risk premia with respect to macroeconomic factors remains an open question for active management.

32 In a very broad sense including cross-skewness and time-skewness management.

10.6.2. *The trend-following strategy with an EWMA trend*

We assume that S_t follows a geometric Brownian motion with constant volatility, but a time-varying unobservable trend:

$$\left\{ \begin{array}{l} \mathrm{d}S_t = \mu_t S_t \,\mathrm{d}t + \sigma S_t \,\mathrm{d}W_t \\ \mathrm{d}\mu_t = \gamma \,\mathrm{d}W_t^{\star} \end{array} \right. \qquad [10.20]$$

We estimate the trend using the exponentially moving average estimator defined as follows:

$$\hat{\mu}_t = \lambda \int_0^t e^{-\lambda(t-s)} \,\mathrm{d}y_s + e^{-\lambda t} \hat{\mu}_0 \qquad [10.21]$$

where $y_t = \ln S_t$ and $\lambda = \gamma/\sigma$. The trend-following strategy is defined by the following nominal exposure:

$$\frac{\mathrm{d}X_t}{X_t} = m \hat{\mu}_t \frac{\mathrm{d}S_t}{S_t} \qquad [10.22]$$

where m is the parameter of position sizing. The exposure is an increasing function of the estimated trend. In particular, we obtain a long portfolio if $\hat{\mu}_t > 0$ and a short portfolio otherwise. Hamdan *et al.* [HAM 16] showed that the performance of the trend-following strategy is equal to:

$$\ln \frac{X_T}{X_0} = m \frac{\left(\hat{\mu}_T^2 - \hat{\mu}_0^2\right)}{2\lambda} + \frac{m}{2} \left(\int_0^T \hat{\mu}_t^2 \left(2 - m\sigma^2\right) \,\mathrm{d}t - \lambda \sigma^2 T \right) \qquad [10.23]$$

We obtain a convex payoff with negative vega. Therefore, the strategy is penalized by the volatility risk. Hamdan *et al.* [HAM 16] also demonstrated that the skewness of this strategy is always positive.

10.6.3. *Skewness aggregation of two log-normal random variables*

We assume that (X_1, X_2) follows a bivariate log-normal distribution. This implies that $\ln X_1 \sim \mathcal{N}\left(\mu_1, \sigma_1^2\right)$ and $\ln X_2 \sim \mathcal{N}\left(\mu_2, \sigma_2^2\right)$. Moreover, we note ρ the correlation between $\ln X_1$ and $\ln X_2$. The skewness of X_1 is equal to:

$$\gamma_1 \left(X_1\right) = \frac{e^{3\sigma_1^2} - 3e^{\sigma_1^2} + 2}{\left(e^{\sigma_1^2} - 1\right)^{3/2}} \qquad [10.24]$$

whereas the skewness of $X_1 + X_2$ is equal to:

$$\gamma_1 (X_1 + X_2) = \frac{\mu_3 (X_1 + X_2)}{\mu_2^{3/2} (X_1 + X_2)} \quad [10.25]$$

where $\mu_n (X)$ is the $n\text{th}$ central moment of X. We can show that:

$$\mu_2 (X_1 + X_2) = \mu_2 (X_1) + \mu_2 (X_2) + 2 \operatorname{cov} (X_1, X_2) \quad [10.26]$$

where:

$$\mu_2 (X_1) = e^{2\mu_1 + \sigma_1^2} \left(e^{\sigma_1^2} - 1 \right) \quad [10.27]$$

and:

$$\operatorname{cov} (X_1, X_2) = (e^{\rho\sigma_1\sigma_2} - 1) e^{\mu_1 + \frac{1}{2}\sigma_1^2} e^{\mu_2 + \frac{1}{2}\sigma_2^2} \quad [10.28]$$

For the third moment of $X_1 + X_2$, we use the following formula:

$$\mu_3 (X_1 + X_2) = \mu_3 (X_1) + \mu_3 (X_2) + 3 (\operatorname{cov} (X_1, X_1, X_2) + \operatorname{cov} (X_1, X_2, X_2)) \quad [10.29]$$

where:

$$\mu_3 (X_1) = e^{2\mu_3 + \frac{3}{2}\sigma_1^2} \left(e^{3\sigma_1^2} - 3e^{\sigma_1^2} + 2 \right) \quad [10.30]$$

and:

$$\operatorname{cov} (X_1, X_1, X_2) = (e^{\rho\sigma_1\sigma_2} - 1) e^{2\mu_1 + \sigma_1^2 + \mu_2 + \frac{\sigma_2^2}{2}} \left(e^{\sigma_1^2 + \rho\sigma_1\sigma_2} + e^{\sigma_2^2} - 2 \right) \quad [10.31]$$

10.6.4. *A skewness model of asset returns*

For modeling the skewness risk of a portfolio, Bruder *et al.* [BRU 16] assume that the vector of asset prices $S_t = (S_{1,t}, \ldots, S_{n,t})$ follows a jump-diffusion process:

$$\left\{ \begin{array}{l} \mathrm{d}S_t = \mathrm{diag}\left(S_t\right) \mathrm{d}L_t \\ \mathrm{d}L_t = \mu \, \mathrm{d}t + \Sigma^{1/2} \, \mathrm{d}W_t + \mathrm{d}Z_t \end{array} \right. \qquad [10.32]$$

where μ and Σ are the vector of expected returns and the covariance matrix, W_t is a n-dimensional standard Brownian motion and Z_t is the irregular component independent from W_t. More precisely, $Z_t = \sum_{i=1}^{N_t} Z_i$ is a pure n-dimensional compound Poisson process with a finite number of jumps, where N_t is a scalar Poisson process with constant intensity parameter $\lambda > 0$, and $Z_1, \ldots, Z_{N_t}$ are vectors of i.i.d. random jump amplitudes with law $\nu\left(\mathrm{d}z\right)$. They also assume that $\nu\left(\mathrm{d}z\right) = \lambda f\left(z\right) \mathrm{d}z$ where $f\left(z\right)$ is the probability density function of the multivariate Gaussian distribution $\mathcal{N}\left(\tilde{\mu}, \tilde{\Sigma}\right)$, $\tilde{\mu}$ is the expected value of jump amplitudes and $\tilde{\Sigma}$ is the associated covariance matrix.

10.6.4.1. *Probability distribution of asset returns*

When λ is sufficiently small, we can show that asset returns[33] $R_t = (R_{1,t}, \ldots, R_{n,t})$ have the following multivariate density function:

$$\begin{aligned} f\left(y\right) &= \frac{1 - \lambda \, \mathrm{d}t}{\left(2\pi\right)^{n/2} \left|\Sigma \, \mathrm{d}t\right|^{1/2}} e^{-\frac{1}{2}\left(y - \mu \, \mathrm{d}t\right)^\top \left(\Sigma \, \mathrm{d}t\right)^{-1} \left(y - \mu \, \mathrm{d}t\right)} \\ &\quad + \frac{\lambda \, \mathrm{d}t}{\left(2\pi\right)^{n/2} \left|\Sigma \, \mathrm{d}t + \tilde{\Sigma}\right|^{1/2}} e^{-\frac{1}{2}\left(y - \left(\mu \, \mathrm{d}t + \tilde{\mu}\right)\right)^\top \left(\Sigma \, \mathrm{d}t + \tilde{\Sigma}\right)^{-1} \left(y - \left(\mu \, \mathrm{d}t + \tilde{\mu}\right)\right)} \end{aligned} \qquad [10.34]$$

It follows that it is equivalent to using a Gaussian mixture distribution for modeling asset returns. There are two regimes:

– the "normal" regime has the probability $(1 - \lambda \, \mathrm{d}t)$ of occurring. In this case, asset returns are driven by the Gaussian distribution $\mathcal{N}\left(\mu \, \mathrm{d}t, \Sigma \, \mathrm{d}t\right)$;

– the "jump" regime has the probability $\lambda \, \mathrm{d}t$ of occurring. In this case, asset returns jump simultaneously and the jump amplitudes are driven by the Gaussian distribution $\mathcal{N}\left(\tilde{\mu}, \tilde{\Sigma}\right)$.

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33 The return $R_{i,t}$ of asset i is defined for the holding period $[t - \mathrm{d}t, t]$:

$$R_{i,t} = \ln S_{i,t} - \ln S_{i,t-\mathrm{d}t} \qquad [10.33]$$

We can show that the two first moments of asset returns are:

$$\mathbb{E}\left[R_t\right] = \mu \,\mathrm{d}t + \pi\tilde{\mu} \tag{10.35}$$

and:

$$\operatorname{cov}\left(R_t\right) = \left(\Sigma + \lambda\tilde{\Sigma}\right) \mathrm{d}t + \lambda\left(1 - \lambda \,\mathrm{d}t\right)\tilde{\mu}\tilde{\mu}^\top \mathrm{d}t \tag{10.36}$$

For the skewness coefficient of asset i, we obtain the following expression:

$$\gamma_1\left(R_{i,t}\right) = \frac{\lambda\left(1 - \lambda \,\mathrm{d}t\right)\left(\left(1 - 2\lambda \,\mathrm{d}t\right)\tilde{\mu}_i^3 + 3\tilde{\mu}_i\tilde{\sigma}_i^2\right) \mathrm{d}t}{\left(\left(\sigma_i^2 + \lambda\tilde{\sigma}_i^2\right) \mathrm{d}t + \lambda\left(1 - \lambda \,\mathrm{d}t\right)\tilde{\mu}_i^2 \,\mathrm{d}t\right)^{3/2}} \tag{10.37}$$

10.6.4.2. *Probability distribution of the portfolio's return*

Let $x = (x_1, \ldots, x_n)$ be the vector of weights in the portfolio satisfying $\sum_{i=1}^n x_i = 1$. We note $R_t(x)$ the portfolio's return:

$$R_t(x) = \sum_{i=1}^n x_i R_{i,t} \tag{10.38}$$

Bruder *et al.* [BRU 16] show that $R_t(x)$ has the following probability density function:

$$\begin{aligned} f(y) &= (1 - \lambda \,\mathrm{d}t)\frac{1}{\sqrt{x^\top(\Sigma \,\mathrm{d}t)\,x}}\phi\left(\frac{y - x^\top(\mu \,\mathrm{d}t)}{\sqrt{x^\top(\Sigma \,\mathrm{d}t)\,x}}\right) \\ &\quad + (\lambda \,\mathrm{d}t)\frac{1}{\sqrt{x^\top\left(\Sigma \,\mathrm{d}t + \tilde{\Sigma}\right)x}}\phi\left(\frac{y - x^\top(\mu \,\mathrm{d}t + \tilde{\mu})}{\sqrt{x^\top\left(\Sigma \,\mathrm{d}t + \tilde{\Sigma}\right)x}}\right) \end{aligned} \tag{10.39}$$

We obtain a Gaussian mixture distribution. We can show that:

$$\mathbb{E}\left[R_t(x)\right] = x^\top\left(\mu + \lambda\tilde{\mu}\right) \mathrm{d}t \tag{10.40}$$

and:

$$\sigma\left(R_t(x)\right) = \sqrt{x^\top\left(\Sigma + \lambda\tilde{\Sigma}\right)x \,\mathrm{d}t + \lambda\left(1 - \lambda \,\mathrm{d}t\right)\left(x^\top\tilde{\mu}\right)^2 \mathrm{d}t} \tag{10.41}$$

For the skewness coefficient, we obtain:

$$\gamma_1 \left(R_t \left(x \right) \right) = \frac{\lambda \left(1 - \lambda \, \mathrm{d}t \right) \left(\left(1 - 2\lambda \, \mathrm{d}t \right) \left(x^\top \tilde{\mu} \right)^3 + 3 \left(x^\top \tilde{\mu} \right) \left(x^\top \tilde{\Sigma} x \right) \right) \mathrm{d}t}{\left(x^\top \left(\Sigma + \lambda \tilde{\Sigma} \right) x \, \mathrm{d}t + \lambda \left(1 - \lambda \, \mathrm{d}t \right) \left(x^\top \tilde{\mu} \right)^2 \, \mathrm{d}t \right)^{3/2}} \qquad [10.42]$$

10.7. Bibliography

[ANG 09] ANG A., GOETZMANN W., SCHAEFER S., Evaluation of Active Management of the Norwegian GPFG, Ministry of Finance, Norway, 2009.

[ANG 14] ANG A., *Asset Management – A Systematic Approach to Factor Investing*, Oxford University Press, Oxford, 2014.

[AMI 02] AMIHUD Y., "Illiquidity and Stock Returns: Cross-Section and Time-Series Effects", *Journal of Financial Markets*, vol. 5, no. 1, pp. 31–56, 2002.

[ASN 14] ASNESS C.S., FRAZZINI A., PEDERSEN L.H., "Quality Minus Junk", SSRN, available at www.ssrn.com/abstract=2435323, 2014.

[BAL 17] BALTAS N., "Optimising cross-asset carry", in JURCZENKO E. (ed.), *Factor Investing*, ISTE Press, London and Elsevier, Oxford, 2017.

[BAN 81] BANZ R.W., "The relationship between return and market value of common stocks", *Journal of Financial Economics*, vol. 9, no. 1, pp. 3–18, 1981.

[BAR 03] BARBERIS N., THALER R.H., "A survey of behavioral finance", in CONSTANTINIDES G.M., HARRIS M., STULZ R.M. (eds), *Handbook of the Economics of Finance*, Elsevier, Amsterdam, 2003.

[BAS 77] BASU S., "Investment performance of common stocks in relation to their price-earnings ratios: a test of the efficient market hypothesis", *Journal of Finance*, vol. 32, no. 3, pp. 663–682, 1977.

[BEK 17] BEKTIC D., NEUGEBAUER U., WEGENER M., WENZLER J., "Common equity factors in corporate bond markets", in JURCZENKO E. (ed.), *Factor Investing*, ISTE Press, London and Elsevier, Oxford, 2017.

[BLA 72] BLACK F., "Capital market equilibrium with restricted borrowing", *Journal of Business*, vol. 45, no. 3, pp. 444–455, 1972.

[BLI 17] BLIN O., LEE J., TEÏLETCHE J., Alternative risk premia investing: from theory to practice, Unigestion Research Paper, 2017.

[BOU 06] BOURGUIGNON F., DE JONG M., "The importance of being value", *Journal of Portfolio Management*, vol. 32, no. 3, pp. 74–79, 2006.

[BRU 16] BRUDER B., KOSTYUCHYK N., RONCALLI T., "Risk Parity Portfolios with Skewness Risk: An Application to Factor Investing and Alternative Risk Premia", SSRN, available at www.ssrn.com/abstract=2813384, 2016.

[BUF 98] BUFFETT W., Lecture at the University of Florida School Business, University of Florida, 1998.

[CAR 97] CARHART M.M., "On persistence in mutual fund performance", *Journal of Finance*, vol. 52, no. 1, pp. 57–82, 1997.

[CAZ 14] CAZALET Z., RONCALLI T., "Facts and Fantasies About Factor Investing", SSRN, available at www.ssrn.com/abstract=2524547, 2014.

[COC 01] COCHRANE J.H., *Asset Pricing*, Princeton University Press, Princeton, 2001.

[COC 11] COCHRANE J.H., "Presidential address: discount rates," *Journal of Finance*, vol. 66, no. 4, pp. 1047–1108, 2011.

[DAN 16] DANIEL K.D., MOSKOWITZ T.J., "Momentum Crashes", *Journal of Financial Economics*, vol. 122, no. 2, pp. 221–247, 2016.

[FAM 92] FAMA E.F., FRENCH K.R., "The Cross-Section of expected stock returns," *Journal of Finance*, vol. 47, no. 2, pp. 427–465, 1992.

[FAM 93] FAMA E.F., FRENCH K.R., "Common Risk Factors in the Returns on Stocks and Bonds", *Journal of Financial Economics*, vol. 33, no. 1, pp. 3–56, 1993.

[FAM 98] FAMA E.F., FRENCH K.R., "Value versus Growth: The International Evidence", *Journal of Finance*, vol. 53, no. 6, pp. 1975–1999, 1998.

[FRA 14] FRAZZINI A., PEDERSEN L.H., "Betting Against Beta", *Journal of Financial Economics*, vol. 111, no. 1, pp. 1–25, 2014.

[FUN 01] FUNG W., HSIEH D.A., "The risk in hedge fund strategies: theory and evidence from trend followers", *Review of Financial Studies*, vol. 14, no. 2, pp. 313–341, 2001.

[GRI 95] GRINBLATT M., TITMAN S., WERMERS R., "Momentum Investment Strategies, Portfolio Performance, and Herding: A Study of Mutual Fund Behavior", *American Economic Review*, vol. 85, no. 5, pp. 1088–1105, 1995.

[HAM 16] HAMDAN R., PAVLOWSKY F., RONCALLI T. *et al.*, "A Primer on Alternative Risk Premia", SSRN, available at www.ssrn.com/abstract=2766850, 2016.

[HAR 16] HARVEY C.R., LIU Y., ZHU H., "...and the cross-section of expected returns", *Review of Financial Studies*, vol. 29, no. 1, pp. 5–68, 2016.

[HEN 93] HENDRICKS D., PATEL J., ZECKHAUSER R., "Hot Hands in Mutual Funds: Short-Run Persistence of Relative Performance, 1974–1988", *Journal of Finance*, vol. 48, no. 1, pp. 93–130, 1993.

[HOU 15] HOU K., XUE C., ZHANG L., "Digesting Anomalies: An Investment Approach", *Review of Financial Studies*, vol. 28, no. 3, pp. 650–705, 2015.

[HOU 17] HOUWELING P., VAN ZUNDERT J., "Factor Investing in the Corporate Bond Market", *Financial Analysts Journal*, vol. 73, no. 2, pp. 100–115, 2017.

[ILM 11] ILMANEN A., *Expected Returns: An Investor's Guide to Harvesting Market Rewards*, John Wiley & Sons, Chichester, 2011.

[ILM 12a] ILMANEN A., "Do Financial Markets Reward Buying or Selling Insurance and Lottery Tickets?", *Financial Analysts Journal*, vol. 68, no. 5, pp. 26–36, 2012.

[ILM 12b] ILMANEN A., KIZER J., "The Death of Diversification Has Been Greatly Exaggerated", *Journal of Portfolio Management*, vol. 38, no. 3, pp. 15–27, 2012.

[ISR 16] ISRAEL R., PALHARES D., RICHARDSON S., "Common Factors in Corporate Bond and Bond Fund Returns", SSRN, available at www.ssrn.com/abstract=2576784, 2016.

[JEG 93] JEGADEESH N., TITMAN S., "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency", *Journal of Finance*, vol. 48, no. 1, pp. 65–91, 1993.

[JEN 68] JENSEN M.C., "The Performance of Mutual Funds in the Period 1945-1964", *Journal of Finance*, vol. 23, no. 2, pp. 389–416, 1968.

[JUR 06] JURCZENKO E., MAILLET B., *Multi-moment Asset Allocation and Pricing Models*, John Wiley & Sons, Chichester, 2006.

[JUR 15] JURCZENKO E., TEÏLETCHE J., "Risk-Based Investing But What Risk(s)", in JURCZENKO E. (ed.), *Risk-Based and Factor Investing*, ISTE Press, London and Elsevier, Oxford, pp. 147–171, 2015.

[KOI 17] KOIJEN R.S.J., MOSKOWITZ T.J., PEDERSEN L.H. *et al.*, "Carry", *Journal of Financial Economics*, 2017.

[KRA 76] KRAUS A., LITZENBERGER R.H., "Skewness Preference and the Valuation of Risk Assets", *Journal of Finance*, vol. 31, no. 4, pp. 1085–1100, 1976.

[LAU 05] LAURICELLA T., "Yale Manager Blasts Industry", *Wall Street Journal*, September 6, 2005.

[LEM 14] LEMPÉRIÈRE Y., DEREMBLE C., NGUYEN T.T. *et al.*, "Risk Premia: Asymmetric Tail Risks and Excess Returns", SSRN, available at www.ssrn.com/abstract=2502743, 2014.

[LUC 78] LUCAS R.E., "Asset prices in an exchange economy", *Econometrica*, vol. 46, no. 6, pp. 1429–1445, 1978.

[MAE 16] MAESO J-M., MARTELLINI L., Factor investing and risk allocation: from traditional to alternative risk premia harvesting, *EDHEC Working Paper*, Nice, 2016.

[MAI 10] MAILLARD S., RONCALLI T., TEÏLETCHE J., "The Properties of Equally Weighted Risk Contribution Portfolios", *Journal of Portfolio Management*, vol. 36, no. 4, pp. 60–70, 2010.

[MAR 52] MARKOWITZ H., "Portfolio Selection", *Journal of Finance*, vol. 7, no. 1, pp. 77–91, 1952.

[MAR 56] MARKOWITZ H., "The Optimization of a Quadratic Function Subject to Linear Constraints", *Naval Research Logistics Quarterly*, vol. 3, nos. 1–2, pp. 111–133, 1956.

[MAR 10] MARTELLINI L., ZIEMANN V., "Improved Estimates of Higher-Order Comoments and Implications for Portfolio Selection", *Review of Financial Studies*, vol. 23, no. 4, pp. 1467–1502, 2010.

[MAR 15] MARTELLINI L., MILHAU V., Factor investing: a welfare improving new investment paradigm or yet another marketing fad?, *EDHEC Working Paper*, Nice, 2015.

[MOS 12] MOSKOWITZ T.J., OOI Y.H., PEDERSEN L.H., "Time Series Momentum", *Journal of Financial Economics*", vol. 104, no. 2, pp. 228–250, 2012.

[MOS 13] ASNESS C.S., MOSKOWITZ T.J., PEDERSEN L.H., "Value and momentum everywhere", *Journal of Finance*, vol. 68, no. 3, pp. 929–985, 2013.

[PAS 03] PASTOR L., STAMAUGH R.F., "Liquidity risk and expected stock returns", *Journal of Political Economy*, vol. 111, no. 3, pp. 642–685, 2003.

[PIO 00] PIOTROSKI J.D., "Value Investing: The Use of Historical Financial Statement Information to Separate Winners from Losers", *Journal of Accounting Research*, vol. 38, pp. 1–41, 2000.

[POT 06] POTTERS M., BOUCHAUD J-P., "Trend Followers Lose More Often Than They Gain", *Wilmott Magazine*, vol. 26, pp. 58–63, 2006.

[RON 13] RONCALLI T., *Introduction to Risk Parity and Budgeting*, Chapman & Hall/CRC, Boca Raton, 2013.

[RON 15] RONCALLI T., "Introducing Expected Returns into Risk Parity Portfolios: A New Framework for Asset Allocation", *Bankers, Markets & Investors*, vol. 138, pp. 18–28, 2015.

[ROS 76] ROSS S., "The Arbitrage Theory of Capital Asset Pricing", *Journal of Economic Theory*, vol. 13, no. 3, pp. 341–360, 1976.

[SCH 07] SCHERER B., *Portfolio Construction & Risk Budgeting*, Risk Books, London, 2007.

[SHA 64] SHARPE W.F., "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk", *Journal of Finance*, vol. 19, no. 3, pp. 425–442, 1964.

11

Strategic Portfolio Allocation With Factors

Traditional asset allocation is burdened by the complexity of dealing with a multitude of available investment options, each reflecting exposure to many different underlying drivers of risk and return. By creating an abstraction of that process via a parsimonious set of factors, investors can focus on the true underlying macroeconomic drivers of risk and return. Allocation decisions are made in factor space and then translated back into an implementable asset allocation while taking into account individual investors constraints and preferences.

11.1. Introduction

The universe of available asset classes, subasset classes and managed funds down to individual securities can extend to thousands of positions, and each security is sensitive to many underlying drivers of risk and return. With all of those asset class choices and all of the many flavors of risk that apply to each, a proper strategic asset allocation process requires an appropriate level of abstraction. Too simple, and the abstraction is useless. Too complex, and the abstraction is not practical.

In this chapter, we show how factors can be used in strategic asset allocation. Factors can allow the investor to take the complexity of traditional asset allocation and replace it with an efficient and intuitive framework that provides a clear path for answering the three fundamental questions of portfolio management: what do I own, what do I want to own, and how do I get there?

Strategic asset allocation approaches, however, still focus on assets rather than factors. According to a global survey by Economist Intelligence Unit, some hurdles for the adoption of a factor-based approach to strategic asset allocation include lack

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of expertise, data and tools[1]. Fortunately, all of these concerns can be addressed through use of modern techniques to enhance the traditional asset allocation approach by reorienting the investor mindset from assets to factors. We will now walk through step by step how the strategic allocation process can be improved through the incorporation of factor analysis.

11.2. Factors

In its rawest form, the calculation and decomposition of risk in an institutional portfolio may involve thousands of individual holdings as well as thousands of underlying factors. However, much of that complexity can be abstracted away from the investor – security level analysis can be replaced by asset class level proxies and then even further simplified by restating in factor terms.

Many factor sets are available for risk analysis. Some factor sets employ thousands of factors, and some offer a more succinct group of factors. Although granular factor sets are crucial for asset-level modeling and risk management, higher level allocation decisions are more efficiently supported by a much smaller set of factors. In particular, macro factors are broad, persistent drivers of return that provide compensation for bearing exposure to non-diversifiable macroeconomic risks. The factors are tangible, applicable across all asset classes and can explain the majority of asset class risk.

One approach to selecting a set of macro factors is to use principal component analysis on a set of global asset class returns[2]. Against this broad set of market returns, the first three principal components explain 75% of cross-asset movements and the first six account for 90%.

Analysis of these largest principal components reveals correlations with macro factors. The first principal component shows a strong correlation with a portfolio of risky assets, particularly global equities. As part of the goal of factor construction is to create a simple and observable factor replicating portfolio, we proxy this first component with a weighted basket of global developed market equities. This replicating portfolio correlates highly with unexpected changes in various GDP measures, and thus it is reasonable to characterize this first factor as proxying economic growth. The second principal component behaves like a portfolio of safe

1 Economist Intelligence Unit, The Rise of Factor Investing, Report, 2016.
2 The 13 global asset classes include Inflation Linked Debt, Developed Sovereign Debt, IG Debt, EM Sovereign Debt, HY Debt, Developed Equity, Developed Small Cap Equity, EM Equity, Private Equity, Infrastructure, Property, Commodities ex-Energy and Energy Commodities. The period from January 1997 to September 2015 across 13 assets was chosen as a practical tradeoff between historical data availability and asset universe coverage.

haven assets, most notably global government and inflation-linked bonds, suggesting the second principal component proxies for real rates and inflation factors. Further analysis of the principal components identifies three additional factors: credit, emerging markets and commodities.

The result of this analysis is a set of six factors that are both economically intuitive as well as replicable with liquid market indices. A set of six factors falls within the range that others (e.g. [BLY 16]) have recommended as being sufficient in terms of explanatory power while still being practical for portfolio construction exercises.

The following six macro factors provide a useful framework for analyzing risk and return of a global, multiasset portfolio:

Economic Growth	Risk associated with global economic growth *Broad-market equity index returns*
Inflation	Risk of bearing exposure to changes in nominal prices *Return of long nominal bonds, short inflation-linked bonds portfolio*
Real Rates	Risk of bearing exposure to real interest rate changes *Inflation-linked bond returns*
Credit	Risk of default or spread widening *Return of long corporate bonds, short nominal bonds portfolio*
Emerging Markets	Risk that emerging sovereign governments will change capital market rules *Basket of EM equity premia, EM CDX and EM FX*
Commodity	Risk associated with commodity markets *Weighted GSCI Commodity index returns*

In addition to these six factors, it is often helpful to include a foreign exchange factor for measuring the risk associated with unhedged developed foreign currency exposure. A basket of currencies including USD, EUR, JPY, GBP, CAD, and AUD is generally sufficient for capturing the majority of this risk.

The macro factors are intrinsically related to a more detailed, underlying risk factor model. While macro factors are intuitive fundamental drivers of return, they exhibit residual risk. At the same time, the thousands of risk factors in the more granular risk model allow for a precise risk measurement with minimal residual risk. Macro factors are shared between asset classes and are optimal for strategic asset allocation. Risk management factors, on the other hand, are asset class specific or even specific to a particular asset itself. They are optimal for zooming in on the smallest details to facilitate better risk management. In the Appendix (section 11.7), we detail the process of mapping security level risk onto risk management factors and then onto macro factors. We create hypothetical factor mimicking portfolios with liquid market instruments in order to track daily risk and return of the factors as well as make *ex ante* statements about volatilities and correlations between the factors.

The strategic asset allocation process can be thought of as a journey through the following three questions:

– *What factors do I own?* Every portfolio analysis should start with understanding the risk and return profile of the current portfolio. Given a portfolio representation as a mix of asset classes, what is the current exposure and risk contribution for both asset classes and factors?

– *What factors do I want to own?* Once an understanding of the current factor exposure and risk profile is determined, the investor can set a desired factor allocation in the context of the investor's unique set of circumstances.

– *How do I get there?* Finally, the investor needs to translate the desired factor mix into a replicating asset class allocation subject to a variety of constraints including determination of investment universe, asset class boundaries and liquidity and expense constraints.

11.3. What do I own?

Investment analysis almost always begins with understanding the current state of the portfolio. Ideally, the investor has detailed information for each investment in the portfolio at their fingertips as well as the tools and technology to quickly and accurately model that data. However, both the transparency and the sheer volume of that data can be prohibitive. Fortunately, portfolios can usually be modeled as a combination of asset class proxies without significant loss of accuracy. These asset class proxies should span all types of investments – equities, fixed income, alternatives in both liquid and illiquid forms – and various regions around the world.[3] Simplifying the portfolio representation in this way avoids the complexities of modeling individual holdings, succinctly summarizes the composition of the portfolio, and allows for easy modifications to the base asset allocation.

3 Although portfolio construction has been simplified, our underlying analyses of the portfolio use security level detail for the greatest degree of accuracy as the asset classes are proxied by real-world indices.

Portfolio analysis can be performed by leveraging asset class or fund proxies based on widely available indices, although some illiquid asset classes may require custom modeling. The list of asset classes should be carefully chosen to be comprehensive and include a wide range of investment types while at the same time being small enough for easy selection.

In practice, a list of approximately 100 asset classes is sufficient to model most portfolios. Working at the asset class level significantly narrows the required inputs. In Figure 11.1, we examine a typical US public defined benefit plan[4]. This portfolio is represented by a selection of asset class proxies, the relative weight of each asset class, an expected return and an assumption about hedging policy[5].

USD 30-Nov-2016

Asset Class	Weight (%)	Exp. Return (%)	FX Hedged
US Large Cap	30.0	4.91	
Global Large Cap ex-US	20.0	5.40	
Global Small Cap	2.0	5.28	
US Aggregate Bonds	20.0	1.85	
Global Aggregate Bonds	3.0	1.88	
Global Private Equity	9.0	5.77	
Global Real Estate	7.0	3.90	
Hedge Funds - Aggressive	4.0	3.20	
Commodities	3.0	2.08	
US Cash	2.0	1.00	
Add Asset Class...	0.0	-	
	100.0		

Figure 11.1. *Sample US public pension plan portfolio (source: BlackRock Aladdin Factor Workbench)*

This concise set of assumptions can produce a robust risk and return analysis in terms of both asset classes and factors, and can allow the investor to analyze the portfolio's risk and return profile through multiple lenses.

4 This peer composite is a hypothetical portfolio, constructed by BlackRock using asset allocation and data sourced from the Pensions & Investments Research Center, specifically the P&I 2014 Top 1000 Retirement Funds.
5 Expected returns are based on the long-term, annualized capital market assumptions produced by the BlackRock Investment Institute, available at: https://www.blackrockblog.com/blackrock-capital-markets-assumptions/.

First, *ex ante* risk is calculated at the portfolio level using traditional variance/covariance methods and expressed as an annualized, one standard deviation measure of volatility. Historical data are used to derive volatilities and covariances among the factors. For strategic asset allocation, use of long time series (i.e. more than 10 years) is appropriate in order to capture time variation across business cycles. The portfolio expected return is computed by weighting expected returns of the individual asset classes by the allocation to each asset class, taking into account the volatility of each asset class and the total portfolio [BER 97].

Figure 11.2 plots the representative pension fund portfolio as an orange diamond on a risk/return chart. The gray square represents a traditional 60/40 reference portfolio with the gray line reflecting an efficient frontier of two reference equity and bond asset classes. This 60/40 portfolio is referred to as a "Reference Portfolio" and has the advantages that it can be implemented at a relatively low cost, is easy to communicate and enables a clear separation of investment responsibilities between benchmark and active management (see [ANG 14]).

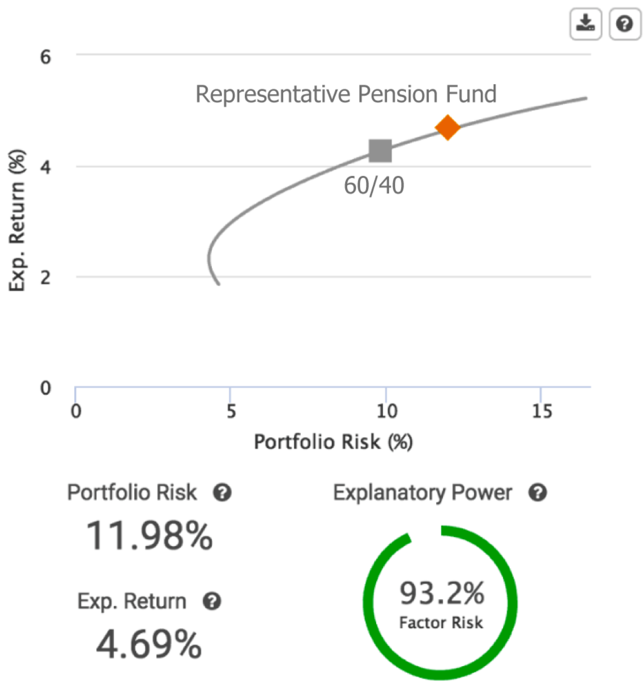

Figure 11.2. *Risk and return characteristics of sample portfolio*

Not all of the risk of a portfolio will be explained with macro factors. The unexplained risk can potentially be attributed to other factors, such as style factors, or to idiosyncratic risk (i.e. risk that is non-systematic and cannot be diversified away). In the sample portfolio, 93.2% of the total risk of 11.98% can be attributed to the macro factors.

Low attribution to the macro factors is not necessarily an indication of poor model performance or an inefficient portfolio. It simply means that the particular portfolio has a higher proportion of risk unexplained by macro factors. This is often seen in portfolios with heavier weightings of alternative asset classes. In fact, certain investors may prefer portfolios with higher proportions of unexplained macro risk as they may not be easily replicated in low-cost investment vehicles (indexes) or macro factor strategies.

Although there are many analyses and decompositions possible for understanding a portfolio's risk, one simple approach is to focus on risk and exposure measurements across both asset classes and factors.

Figure 11.3 represents a visualization of asset class risk and exposure using horizontal bar charts as a clear way to compare magnitude across variables. The *asset allocation* chart (top) shows the capital allocated to each of the asset classes in the portfolio in terms of relative weight. The *contribution to portfolio risk by asset class* chart (bottom) translates that allocation into risk terms by taking into account the volatilities of and correlations between each of the asset classes in addition to the asset class weights. The values in this chart are additive to the total portfolio risk of 11.98%. In particular, the largest contributors to portfolio risk are all forms of equity: US Large Cap Equity (37% of total), Global Large Cap ex-US Equity (29% of total) and Global Private Equity (20% of total). The remaining 14% of risk comes from the remaining asset classes.

Figure 11.3 makes clear that capital allocation can be misleading in terms of predicting actual sources of risk: the allocation to fixed income asset classes actually contributes a negligible amount of risk, whereas the equity and alternative holdings carry a disproportionately high amount of the risk – allocation to equities represent 52% of the portfolio but contribute almost 70% of the risk. Figure 11.3 illustrates the potential danger of thinking only in asset allocation terms by ignoring the true drivers of risk in a portfolio as well as their respective magnitudes. In Figure 11.4, we examine the macro factor risks of the portfolio.

These charts express analogous exposure and risk contribution views, but now in factor terms. The *portfolio beta to factor returns (normalized)* chart (top) shows the beta of the portfolio to each macro factor. The betas are normalized to sum to 100% in order to facilitate relative comparison between portfolios. This shows us that the highest relative sensitivity of the portfolio is to economic growth, with a normalized beta weighting of 47%, and the smallest to emerging markets with a normalized beta weighting of 3% (alternatively, the betas could be shown without normalization to highlight absolute exposures).

Most importantly, the *contribution to portfolio risk by factor* chart (bottom) shows the resulting risk contributions of each factor to the total portfolio risk. Economic growth dominates from a risk perspective and contributes 9.32% out of the total 11.98% risk. The inflation factor provides some risk offset (–0.45%) due to its negative correlation with the other factors.

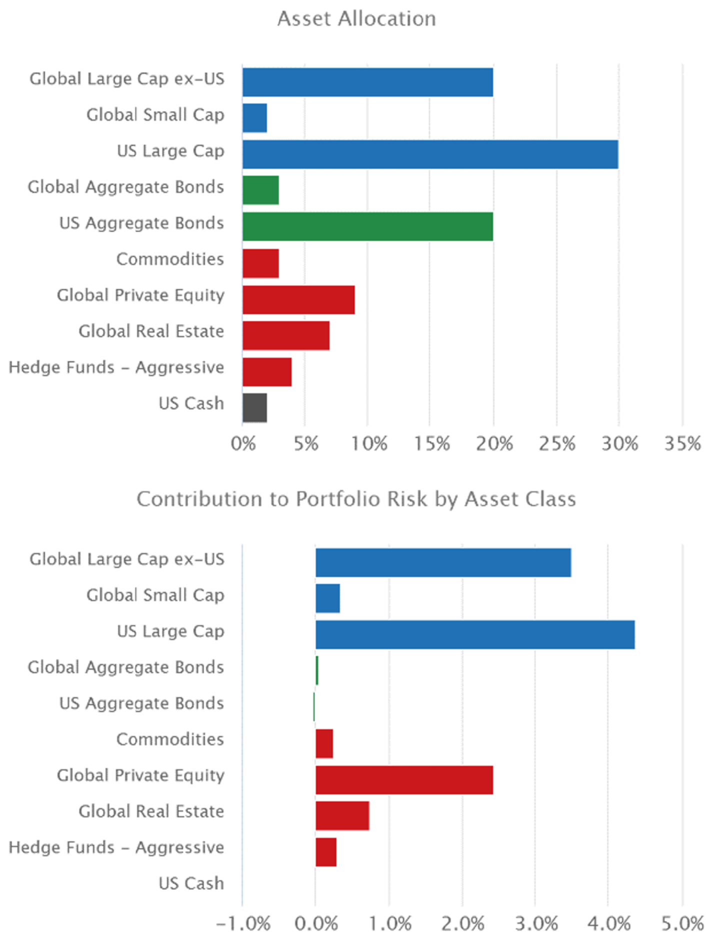

Figure 11.3. *Asset class exposure and risk contribution of sample portfolio*

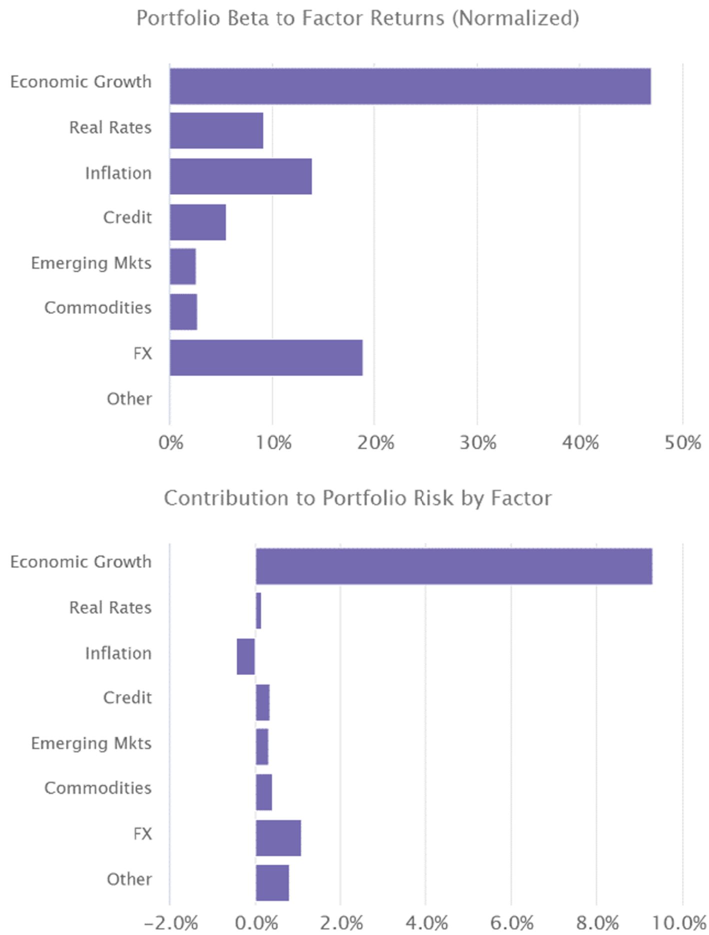

Figure 11.4. *Macro factor exposure and risk of sample portfolio*

In addition to looking at risk through both an asset class lens and a factor lens, it is also critical to understand the linkage between them. Translation between asset classes and factors should be transparent and readily available if the investor is to understand the impact of their decisions. Figure 11.5 provides an example of a visualization of how a single asset class (private equity) in our sample portfolio loads onto the macro factors in both exposure and risk terms. In particular, private equity loads onto economic growth, real rates, emerging markets, and FX macro factors.

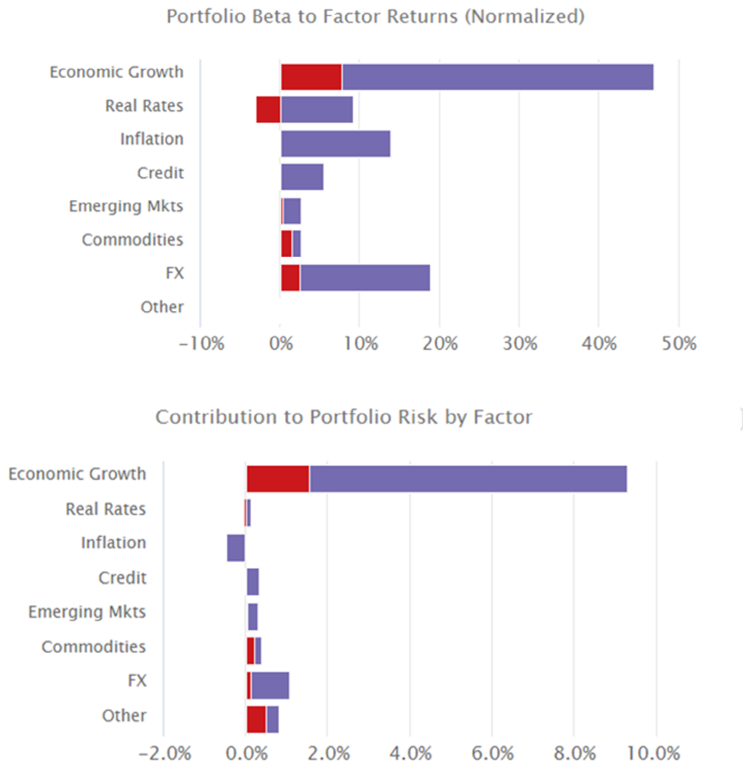

Figure 11.5. *Red shading indicates loading of private equity onto macro factors of sample portfolio. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

11.3.1. *Scenario analysis*

In addition to analyzing asset class and factor risk in terms of volatility, covariances and betas, it is also critical to think about drawdown or tail risk. Scenario analysis subjects the portfolio to a specified set of shocks to the underlying factors. These shocks may be drawn from periods in history or may be hypothetical constructs based on past, current or future plausible market conditions. Decomposing scenario risk across a handful of factors provides an intuitive linkage between real-world economic forces and the risk of the portfolio.

The scenario analysis in Figure 11.3 provides a sampling of economic events the investor may be concerned about and a parametric calculation of how the portfolio would theoretically perform in each scenario[6]. The black diamond in each scenario represents the total gain or loss for the portfolio. The colored sections of each bar show the contribution to that total from each of the macro factors.

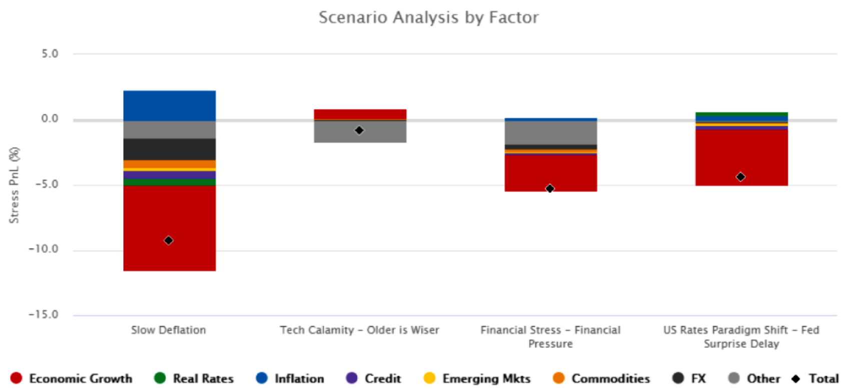

Figure 11.6. *Stress scenario performance of sample portfolio. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

In this group of hypothetical scenarios – slow deflation, tech calamity, financial stress, and a fed surprise delay – the portfolio is expected to underperform in all cases. Economic growth exposure accounts for most of that underperformance in three of the four scenarios while inflation exposure provides risk mitigation in some of the scenarios. For example, consider the slow deflation scenario. In this scenario, oil prices are kept unchanged, the 10-year inflation rate drops 200 bps, the 10-year nominal rate drops to historical lows while short-term nominal rates are held constant and agency mortgage rate spreads tighten. The total expected loss under such conditions is estimated to be 9.26%. The economic growth factor by itself loses 6.49%. However, some loss is offset by a 2.26% gain from the inflation factor.

6 Scenarios have been chosen based on risks relevant to a hypothetical investor based on the composition of the sample portfolio and desire to protect against downside risk. Stress test performance is determined by the implied shock to each risk factor that the portfolio is exposed to. Relationships between risk factors and implied shocks are derived using historical correlations and BlackRock analysis. Slow Deflation depicts a hypothetical scenario where oil prices are stable, 10-year inflation drops 200 basis points and the 10-year nominal rate drops to historic lows while short-term rates are held constant. Tech Calamity–Older is Wiser depicts a hypothetical scenario where North American “new tech” companies underperform “old tech” companies due to weak fundamentals and negative sentiment. Financial Stress–Financial Pressure represents a hypothetical scenario where negative rate pressure on bank profits that curbs credit creations. US Rates Paradigm Shift–Fed Surprise Delay depicts a hypothetical scenario where the Fed unexpectedly does not raise rates post the 2016 US election; the US curve flattens, equity markets sell off mildly, emerging market debt rallies and the US dollar sells off.

If these scenarios represented the investor's primary concerns in the current market environment, then a reduction in exposure to economic growth along with a more balanced exposure to the other factors may help offset those concerns.

11.4. What do I want to own?

Understanding what the investor should own follows next. A factor investing approach allows the investor to focus on the true drivers of risk and return, and each investor's ideal factor allocation is unique as it is a function of risk and return targets and investment constraints that differ among institutions. Some investors are simply trying to maximize Sharpe ratios subject to risk constraints and drawdown limitations. Other investors must account for liability matching and surplus risk.

Although these challenges could be addressed in terms of asset allocation, approaching them within a factor allocation framework helps simplify the problem. By narrowing the investor's universe of choices from dozens of asset classes with highly overlapping characteristics to a handful of factors that are more lowly correlated, the optimized outcome is more robust and may be more easily achieved.

It is also worth noting that for those investors concerned with liability matching such as insurance companies or pension plans, asset and liability management can be more intuitively achieved by expressing both assets and liabilities in terms of factors which more accurately capture liability risk than the underlying market instruments. For example, insurance liabilities are often modeled in terms of cash flow projections or replicating treasury strip portfolios. But, this only captures the interest rate related risk of the liabilities and says nothing about the impact of broader economic forces. It is often more instructive to think about liabilities in terms of economy-wide macro factors.

In our sample portfolio, the factor exposure is unbalanced – the portfolio is heavily overweight the economic growth factor. Diversifying more evenly across the factors allows for a more efficient portfolio – the investor can seek to reduce risk without sacrificing return, or seek to increase return for a given risk level.

The analysis starts with understanding the correlation structure of the macro factors in Figure 11.7[7]. The correlation between economic growth and real rates is very low at 0.04, the correlation between economic growth and inflation is significantly negative at (–0.53), and the correlation between and inflation and credit is also negative (–0.67). The sample portfolio can be diversified by replacing exposure to economic growth with exposures to real rates, inflation and credit.

7 Calculated using 180 months of equally weighted data ending November 30, 2016.

	Economic growth	Real rates	Inflation	Credit	Emerging markets	Commodity
Economic growth	**1**	0.04	–0.53	0.72	0.64	0.32
Real rates	0.04	**1**	–0.19	0.11	0.12	0.17
Inflation	–0.53	–0.19	**1**	–0.67	–0.42	–0.49
Credit	0.72	0.11	–0.67	**1**	0.56	0.43
Emerging markets	0.64	0.12	–0.42	0.56	**1**	0.35
Commodity	0.32	0.17	–0.49	0.43	0.35	**1**

Figure 11.7. *Correlation structure of macro factors. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

Figure 11.8 compares a hypothetical portfolio with a more balanced set of factor exposures to the original sample portfolio. The impact on risk allocation is significant: total risk decreases from 11.98 to 9.69% without sacrificing expected return, which is approximately 4.7% for both the new portfolio and the original sample portfolio.

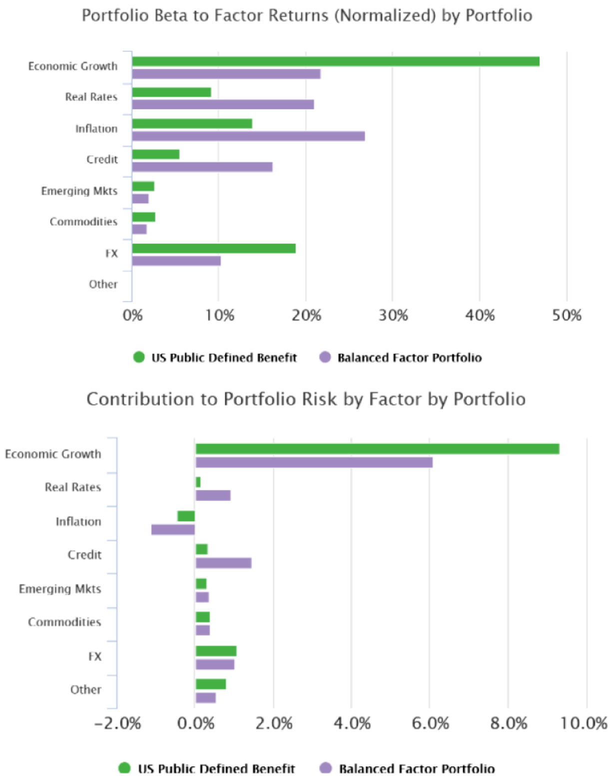

Figure 11.8. *Balanced factor portfolio versus sample portfolio. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

11.5. How do I get there?

An investor generally trades in market instruments, not factors, and so the last step of the investment process is to implement the factor allocation goals with investable securities. Although two investors may have the same desired factor allocation, constraints and preferences unique to each investor will drive them toward different asset allocations. Primary considerations that may differ among investors include risk tolerance, return targets, liquidity preferences and investment universe restrictions.

As discussed above, our sample portfolio will benefit from a more balanced factor allocation – less economic growth exposure offset by more real rates, inflation and credit risk. One example of an asset class with exposure to these three desired macro factors is US Long Credit. Figure 11.9 shows that US Long Credit exposures are evenly distributed between real rates, inflation and credit, with most of the risk attributed to real rates. US Long Credit also provides upside return across the scenario suite previously analyzed.

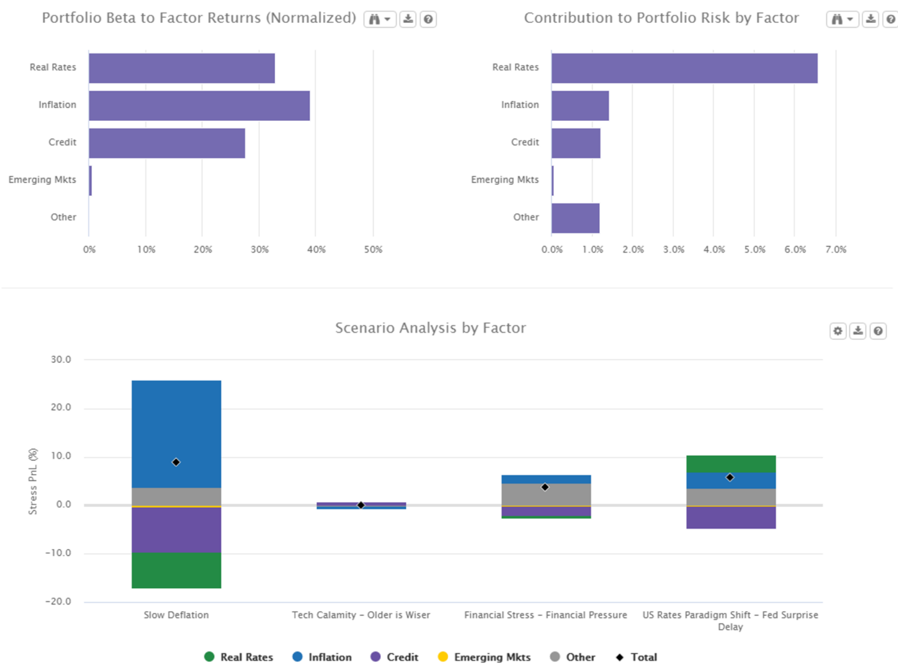

Figure 11.9. *Factor exposure, risk contribution and scenario analysis of US Long Credit. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

In Figure 11.10, we show the mitigation on the downside scenario events for a new portfolio reallocating 15% of Global Large Cap ex-US and 5% US Large Cap asset classes into US Long Credit. (This is the same proposed portfolio that we examined as an improvement over the original sample portfolio in Figure 11.8.) The modified portfolio has less downside performance in each of the scenarios. For example, in the slow deflation scenario portfolio loss improves from –9.3 to –5.2%.

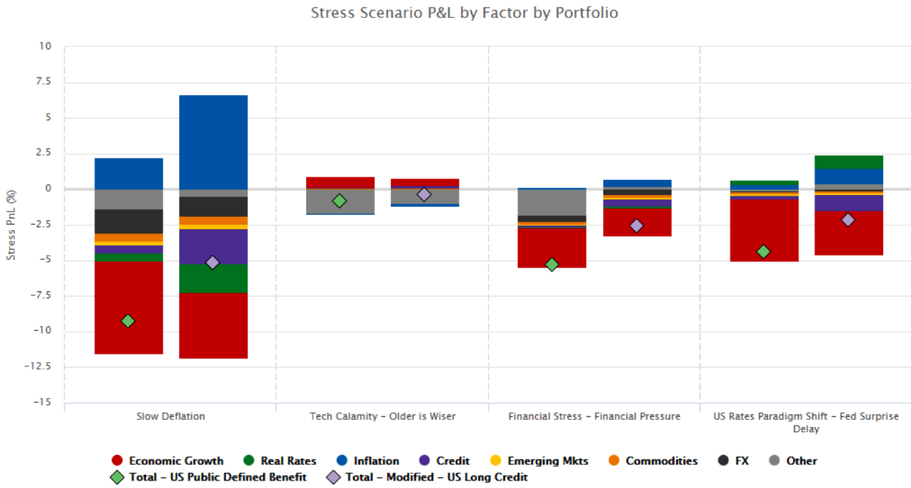

Figure 11.10. *Comparison of stress scenario performance between original and modified sample portfolios. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

In Figure 11.11, we plot the risk and return of the original portfolio (green) along with the new portfolio with US Long Credit (purple). The expected return of the two portfolios is similar (4.69% for the original portfolio vs. 4.63% for the modified version) despite the significant drop in risk (11.98% vs. 9.69%).

An important advantage of the top–down factor allocation process is that if affords the investor an extra degree of freedom in terms of asset allocation. If policy or objectives are defined in factor terms, the investor can reoptimize the asset allocation as market conditions change and particular asset classes become relatively more advantageous or disadvantageous for the investor. For example, we can replace US Long Credit in our modified portfolio with Emerging Market Debt and achieve approximately the same end result in factor space. Figure 11.11 shows the result by replacing US Long Credit (purple) with Emerging Market Debt (orange).

Again, we obtain a reduction in risk from the original portfolio with only a minor expected return penalty.

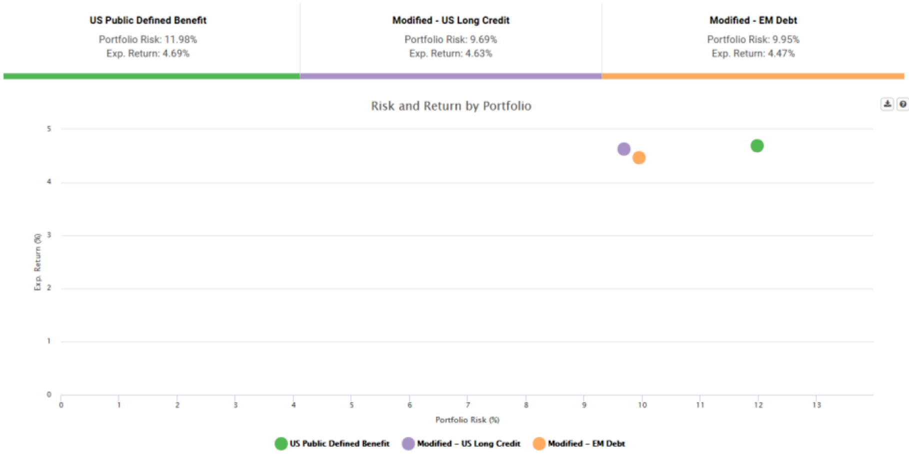

Figure 11.11. *Risk and return comparison. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

This example utilized a simple asset class substitution, but more advanced techniques are now available leveraging optimization techniques that can account for a complex set of objectives and constraints [GRE 16]. These advancements allow investors to take full advantage of the extra degrees of freedom a factor investing approach allows for. By not being locked into a specific asset allocation policy, investors can adjust asset allocation and move between markets to benefit from relative advantages that may arise between asset classes.

11.6. Conclusion

Although institutional portfolios typically consist of thousands of individual holdings, there are only a few true drivers of investment performance and risk – the underlying factors. In particular, focusing on a parsimonious set of macro factors – economic growth, real rates, inflation, credit, emerging markets, commodities and taking into account FX exposure – allows investors to understand the factors that they currently own, inform what the optimal factor exposures should be, and when appropriately mapped to a set of investible assets, can help investors move from their current portfolios closer to what is optimal.

11.7. Appendix

The risk factor model is estimated at the security level. The return of each security r_s is mapped to sensitivities to risk factors.

$$r_s = \sum_f e_{sf} F_f + \varepsilon_s \tag{11.1}$$

Here, e_{sf} is sensitivity, or exposure, of security *s* to risk factor *f*, and F_f is the return of factor *f*. Examples of risk factors are foreign exchange rates, key interest rates, spreads and implied interest rate volatilities. Corresponding examples of exposures are percent market values, key rate durations, spread durations and normal volatility durations.

The transformation of risk factors to macro factors starts with partitioning. First, risk factors are arranged into groups. Examples of groups are developed market rates, emerging market spreads, private and public equity. The parametric return from each group is then separately regressed onto the six macro factors plus FX factor deemed appropriate for that group in order to calculate group-level exposures to the macro factors.

$$F_i = b_{i1} f_1 + b_{i2} f_2 + \cdots + b_{i6} f_6 + b_{iFX} f_{FX} + \nu_i \tag{11.2}$$

Here, b_{ij} represents loading of macro factor f_j on granular factor F_i.

For example, developed market rates risk factors are regressed on real rates and inflation macro factors, and emerging market spreads are regressed on credit and emerging market factors.

Finally, the exposure from each group is then aggregated to arrive at asset class and portfolio level macro factor exposures.

All regressions performed in the mapping process utilize a 15 years, equally weighted monthly covariance matrix. To minimize spurious mappings, a stepwise regression process is used to exclude factors that do not contribute at least 1% to the R-squared of the regression.

The relationship between the Aladdin macro factor model and Aladdin granular risk model is essential for understanding risk decomposition.

Exposures of securities are aggregated into exposures of asset classes, and exposures of asset classes are aggregated into portfolio exposures.

$$\boldsymbol{e}_p \stackrel{\text{def}}{=} \sum_a \boldsymbol{e}_a = \sum_a \sum_f e_{af} \boldsymbol{e}_f \tag{11.3}$$

Here, $\boldsymbol{e}_p$ is the vector of portfolio exposures, $\boldsymbol{e}_a$ are vectors of asset class exposures, e_{af} is scalar exposure of individual asset class a to factor *f* and $\boldsymbol{e}_f$ is a unit vector with exposure to factor *f* set to one and all other element set to zero. This relationship holds for both Aladdin granular risk model and Aladdin macro factor model.

Portfolio risk is a function of systematic and idiosyncratic components. For the purpose of this presentation, we will ignore idiosyncratic component and define portfolio risk as follows:

$$\sigma_p = \sqrt{\boldsymbol{e}_p^T \cdot \Omega \cdot \boldsymbol{e}_p}, \qquad [11.4]$$

where Ω is a covariance matrix of risk factors.

We can decompose portfolio risk into a sum of risk contributions as follows:

$$\sigma_p = \sum_a \sum_f CR_{af}, \qquad [11.5]$$

where the risk contribution of an asset class a with exposure to risk factor f is defined by:

$$CR_{af} \stackrel{\text{def}}{=} \frac{\partial \sigma_p}{\partial e_{af}} e_{af} \qquad [11.6]$$

We can illustrate risk decomposition calculations using an example presented in Table 11.1. We construct a sample 60/40 portfolio consisting of four asset classes – Large Cap and Small Cap US Stocks, US Treasury Bonds and US Inflation-Linked Bonds. For the purpose of this example, we assume that the asset classes have exposure to three risk factors – economic growth, real rates and inflation. Portfolio risk is 8.03%, which is the sum of risk contributions from asset classes and factors, as presented in Table 11.1.

		Risk contribution			Asset class risk contribution (%)
Asset class	Weight (%)	Economic growth (%)	Real rates (%)	Inflation (%)	
US Large Cap	30	3.80			3.80
US Small Cap	30	3.99			3.99
US Treasuries	20		0.20	–0.28	–0.08
US Inflation-Linked Bonds	20		0.31	0.01	0.32
Factor risk contribution		7.79	0.51	–0.27	8.03

Table 11.1. *Risk contribution example for a simplified 60/40 portfolio*

By defining asset class risk contribution as

$$CR_a = \sum_f \frac{\partial \sigma_p}{\partial e_{af}} e_{af} \qquad [11.7]$$

we can look at portfolio risk through the asset class lens (last column of Table 11.1):

$$\sigma_p = \sum_a CR_a \qquad [11.8]$$

When we are dealing with the Aladdin granular risk model with thousands of factors, the asset class lens is more intuitive.

At the same time, if we define *factor risk contribution* as

$$CR_f = \sum_a \frac{\partial \sigma_p}{\partial e_{af}} e_{af} \qquad [11.9]$$

we can easily switch to the factor lens (last row of Table 11.1):

$$\sigma_p = \sum_f CR_f \qquad [11.10]$$

This decomposition holds for both granular factors and macro factors. At the granular level, the factor decomposition is not intuitive. But, by transforming granular risk factors into a small set of macro factors, we gain additional insight from looking through the factor lens.

11.8. Bibliography

[ANG 14] ANG A., *Asset Management: A Systematic Approach to Factor Based Investing*, Oxford University Press, New York, NY, 2014.

[BER 97] BERNSTEIN W.J., WILKINSON D.J., Diversification, rebalancing, and the geometric mean frontier, Working Paper, available at SSRN: http://ssrn.com/abstract=53503, 1997.

[BLY 16] BLYTH S., SZIGETY M., XIA J., "Flexible indeterminate factor-based asset allocation", *Journal of Portfolio Management*, vol. 42, no. 5, pp. 79–93, 2016.

[GRE 16] GREENBERG D., BABU A., ANG A., "Factors to assets: mapping factor exposures to asset allocations", *Journal of Portfolio Management*, vol. 42, no. 5, pp. 18–27, 2016.

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12

A Macro Risk-Based Approach to Alternative Risk Premia Allocation

Alternative risk premia are encountering growing interest from investors. The vast majority of academic literature has been focusing on describing the alternative risk premia (typically, momentum, carry and value strategies) individually. In this chapter, we investigate the question of the allocation across a range of cross-asset alternative risk premia. For this, we design an active macro risk-based framework that notably aims to exploit alternative risk premia's varying behavior in different macro regimes. We build long-term strategic portfolios across economic regimes, which we dynamically tilt based on point-in-time signals related to regimes nowcasting and current carry. We perform back tests of the allocation strategy in an out-of-sample setting.

12.1. Introduction

Alternative risk premia investing has grown rapidly in popularity in the investment community in recent years. They encompass solutions mimicking investment strategies formerly available through investment in hedge fund vehicles but proposed with terms more favorable to investors, notably in terms of liquidity or management fees[1].

Alternative risk premia have not developed from complex financial engineering developments. Rather, they tend to be well known, empirically tested and associated with regularities that have frequently been widely analyzed in academic research. This started with the ground-breaking research of Fama and French [FAM 92] on

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1 For general introduction to alternative risk premia and their practical use, see [RON 17] or [BLI 17].

equity factors[2] and has largely flourished with extensions to other investment styles and factors such as carry [KOI 17], value or momentum [ASN 13a].

The vast majority of the academic literature focuses solely on the identification and the analysis of individual alternative risk premia strategies. Rather than further contributing to the "zoo of factors" [COC 11, HAR 15], this chapter addresses the question of the allocation among alternative risk premia. The standard approach in the industry is to apply a risk-based allocation mechanism, and most notably equal risk contribution (ERC) which allocates the same risk budget to all components in the portfolio [MAI 10]. One of the perceived key benefits of this approach is that it does not require expected returns as input but solely risk measures, hence the name "risk based". The benefit for investors of this agnostic or "no-views" feature is that it alleviates the pitfalls of forecasting, which is already a challenge for traditional assets but even more so for alternative risk premia that are newer or are perceived as more complex strategies.

Our objective in this chapter is to provide investors with an allocation framework for alternative risk premia. In the literature, very few attempts have been made to try to exploit asset allocation among alternative risk premia. Gnedenko and Yelnik [GNE 14] propose a dynamic allocation model between carry, value and momentum mainly based on their recent performance (momentum). Carhart *et al.* [CAR 14] offer a more complete model, both by using a larger set of alternative ("exotic" in their terminology) risk premia and by adding a broader set of tactical indicators in addition to momentum, with notably carry, valuation and sensitivity to risk-aversion events (called "spillover" risk in their article).

In this chapter, we extend those results by focusing on the relationship between alternative risk premia and macroeconomic regimes. Our approach, which we label "macro risk-based", mostly relies on the estimation of the sensitivity of alternative risk premia to a set of economic and market regimes that correspond to major macroeconomic risk factors, and how to implement dynamic risk budgeting decisions on this basis. We draw on recent advances in the literature on risk-based investing, and particularly the framework designed in [JUR 14] that allows investors to combine a pure risk-based approach with a set of views on the portfolio

2 It is important to contrast the concept of risk premia with the concept of a factor frequently used in the asset management industry as well. The "factor" is the fundamental explanation behind the existence of the risk premia. For instance, the so-called "term premium" risk premia is justified by the fact that bond investors are exposed to inflation risk. Here, inflation is the factor and the term premium is the associated risk premium. Similarly, investors in corporate bonds collect the credit risk premium in exchange for being exposed to the default risk of the bond issuer (the factor).

components in a Black–Litterman framework. For this, we start by defining a long-term strategic risk budget allocation that we dynamically tilt based on two major types of point-in-time signals: nowcasting indicators of macroeconomic regimes and the current carry of alternative risk premia. We perform back tests of the strategy in an out-of-sample setting across a diversified range of cross-asset alternative risk premia strategies over the period 2005–2016.

The rest of the chapter is organized as follows. Section 12.2 reviews the academic literature. Section 12.3 describes the construction and the main empirical characteristics of the alternative risk premia used in this analysis. Section 12.4 details our definition of economic regimes and shows how alternative risk premia react to them. Section 12.5 introduces and applies our macro risk-based framework. Section 12.6 concludes this chapter.

12.2. Literature review

The starting point of the academic literature on alternative risk premia is frequently associated with the analysis of Fama and French [FAM 93], which showed that the performance of stocks can be explained by the exposures of the securities to three main factors: the market evolution, the spread of performance between value companies and growth companies, and the spread of performance between companies with small versus large capitalization, respectively. Carhart [1997] identified that the momentum in stocks was also a differentiating and rewarded factor across stocks. Piotroski [PIO 00] and Novy-Marx [NOV 13] show that high-quality companies (highly profitable or with low risk) tend to outperform junk companies. All in all, equity indices provide incomplete exposure to these various sources of return[3]. The objective of the alternative risk premia approach is to magnify them by removing the effect of the market directionality and bringing the portfolio to the chosen risk target.

3 This is evident for traditional market capitalization weighted indices, but also valid for so-called “smart beta” strategies. The latter are long-only portfolios that apply alternative weighting schemes - as opposed to the conventional market capitalisation weights. This way, smart beta strategies have mixed exposure to both traditional and alternative risk premia. For instance, a value smart beta portfolio will be fully-invested in a selection of single stocks with the best scores in terms of some value criteria (e.g. price-to-book). As it is a long-only portfolio of stocks extracted from the same universe, the correlation to the equity market capitalization index will remain fairly high (0.7 or higher) and the exposure to the value risk premia is only partial. By removing the effect of market directionality, alternative risk premia give a purer exposure to the return potential of the risk premium they exploit.

More recently, academics and practitioners have identified similar types of patterns across a broader set of asset classes. There is very ample evidence showing that (directional) momentum investing can be exploited successfully in a cross-asset setting [BAL 13, BAL 15, HUR 13, MOS 12, LEM 14]. In practice, the strategies replicate trend-following methodologies that have been implemented for many decades by hedge funds managers, and more specifically commodity trading advisors and some global macro traders.

Carry investing has also been identified as another strategy set that is systematically rewarded in the long run. The carry is the return an investment provides should its price (or other relevant market conditions such as yield curve for fixed income) remains the same, i.e. a form of income associated with the investment. The carry of a real estate investment will be the rent it provides. For bonds or equities, the carry will be closely related to the regular payments offered to the investor such as coupons or dividends[4]. In foreign exchange markets, the carry is associated with the short-term interest rate paid on the currency. The evidence on the profitability for carry strategies indeed started in foreign exchange markets, with the well-known currency forward rate bias literature that documents that high interest rate currencies tend to outperform low interest rate ones [HAN 80, MEE 83]. This notably contradicts the uncovered interest rate parity theory but, maybe more interestingly for practitioners, this opens the door to profitable strategies. Indeed, in such an environment, the investor can create profitable portfolios by going long the high-yielding currencies and short the low-yielding ones. Here again, the strategy has been applied in practice by global macro hedge fund managers. More globally, Koijen *et al*. [KOI 17] have recently shown that the profitability of carry strategies is valid for a large range of asset classes (fixed income, equities, commodities and foreign exchange).

The concept of value investing has also been shown to be profitable elsewhere than in equities, and typically in foreign exchange markets. While value can be defined in many different ways for currencies, a common practice is to rely on purchasing power parity (PPP) models that state that exchange rates shall equalize purchasing powers in the different economies. While evidence on the verification of the PPP is mixed, empirical validation looks more accepted at longer horizons. Patient investors can then be rewarded in the long run by going long currencies whose values are below the ones implied by PPP and shorting the ones whose values are above their PPP-consistent exchange rates.

After the identification of alternative risk premia, it is natural to question their sensitivity to the economic and market environments. Traditional risk premia have

4 We give more precise definitions of carry for the various asset classes later in the text.

been shown to display time-varying characteristics mainly related to business cycle dynamics and regimes (see, among others, [ANG 04, KRI 12]). Similar patterns have been revealed for some alternative risk premia such as equity momentum [WAN 10] or value growth [ASN 00].

Very few studies have been investigating this dimension of alternative risk premia from a cross-asset perspective. Ebner [EBN 16] shows that risk premia (in practice, a mix of traditional risk premia and alternative risk premia) react to changes in industrial production, inflation, market volatility and liquidity. Asness *et al*. [ASN 13a] find limited evidence on the impact of macro variables (such as consumption or GDP growth) on value and momentum cross-asset returns, but a strong effect of liquidity indicators. On the contrary, Ahmerkamp *et al*. [AHM 12] show that business cycle predictors (dividend yield, short rate, term structure, default spread) and liquidity variables have strong explanatory power for strategies that combine carry and momentum across asset classes. Koijen *et al*. [KOI 17] also show that global carry returns (aggregated across asset classes) tend to be significantly lower during economic downturns and poor liquidity events. Cooper *et al*. [COO 16] show that cross-asset value and momentum portfolios load significantly on global macroeconomic risk factors (industrial production, unexpected inflation, change in expected inflation, term spread, default spread). Interestingly, the authors prove that these loadings justify important stylized facts such as the negative correlation between value and momentum.

In the rest of this chapter, we extend those results. We start with a presentation of our set of alternative risk premia in section 12.3.

12.3. Alternative risk premia construction and empirical characteristics

In this section, we first describe how we construct our alternative risk premia and then analyze the general characteristics of their returns.

12.3.1. *Alternative risk premia construction*

The list of alternative risk premia, their construction and implementation are described in Table 12.1. They cover equity factors, cross-asset trend following (directional momentum), foreign exchange value and a range of carry strategies across rates, credit, developed and emerging currencies, dividends and equity volatility. All alternative risk premia are individually scaled to 10% volatility. Our risk model is based on exponentially weighted volatilities using a decay factor of

0.97, which corresponds to a half-life of 1 month, and correlations based on an expanding window of weekly returns. We use weekly returns for correlations in order to avoid underestimating correlation dynamics between assets traded in different time zones. Every alternative risk premia is rebalanced at the end of each calendar month, and their weights are allowed to drift until the next rebalancing. The sample period spans from January 1999 to December 2016 for most alternative risk premia, with the exception of credit carry (November 2005–December 2016), dividends carry (August 2008–December 2016) and volatility carry (June 2004–December 2016) due to limitations in data availability.

Strategy	Investment universe	Process	Implementation
Equity quality	MSCI World	Rank stocks across profitability (ROE, EBITDA margin, accruals) and safety (Debt/EBITDA, asset leverage). Long first quintile, short bottom quintile.	Long/short single stocks
Equity momentum	MSCI World	Rank stocks on 1-year excluding 1-month mean-reversion, and adjusted for volatility. Long first quintile, short bottom quintile.	Long/short single stocks
Equity size	MSCI World	Rank stocks across market capitalization, enterprise value, total assets. Long first quintile, short bottom quintile.	Long/short single stocks
Equity value	MSCI World	Rank stocks across dividend yield, EV/EBITDA, price/book, price/sales, price/FFO. Long first quintile, short bottom quintile.	Long/short single stocks
Trend following	Long-term rates, credit indices, equity indices, FX	Long assets with positive trend, short assets with negative trend. Trend = average of sign of 1 year and 3 months past performance.	Bonds futures, CDS indices, equity index futures, FX futures, and FX forwards
FX value	G10 FX	Long most undervalued currencies, short most overvalued currencies on a cross-sectional basis (i.e. always long and short even if all currencies under or over-valued). Valuation computed as the ratio between spot rates and OECD PPP rates.	FX futures
Bonds carry	Long-term rates	Long rates with above median carry, short rates with below median carry. Higher absolute weights for rates with largest difference from median. Duration neutral portfolio.	Bonds futures

Credit carry	CDS on Europe and North America indices	Long high yield (HY) credit indices, short investment grade (IG) credit indices. Risk-based ratio HY versus IG weightings.	CDS indices
DM FX carry	G10	Long currencies with above median carry, short currencies with below median carry. Higher absolute weights for currencies with largest difference from median.	FX futures and forwards
EM FX carry	Emerging countries	Long currencies with above median carry, short currencies with below median carry. Higher absolute weights for currencies with largest difference from median.	FX forwards
Dividends carry	EuroStoxx 50	Long a synthetic 1 year constant maturity EuroStoxx 50 dividend future, short EuroStoxx 50 futures. Risk-based ratio of EuroStoxx 50 to Dividend futures based on 22-day beta	Dividends and index futures
Volatility carry	S&P 500	Short (long) VIX futures and S&P 500 futures when VIX in contango (backwardation). Risk-based ratio of S&P 500 to VIX futures	VIX futures, S&P 500 futures

Note: The table gives the list and the composition of the various alternative risk premia used in the chapter.

Table 12.1. *Alternative risk premia description*

Equity factors are implemented as long-short portfolios of single stocks, where the long and the short portfolios are, respectively, based on the first and last quintiles of stocks in the universe when stocks are ranked according to the factor. Four families of factors are considered with value, momentum, quality and size, corresponding to some of the most popular equity investment styles. However, our measures remain different from standard ones used in the academic literature for two major reasons. First, the stocks are picked in a global (MSCI World) universe while standard factors used in the academic literature most frequently focus on US stocks only. Second, our measures incorporate various robustness improvements. For instance, the fact that we condition momentum signal on volatility provides less sensitivity to short covering episodes, which are at the origin of typical momentum crashes [DAN 16]. Another striking example is equity value where the use of a broader set of indicators aims to reduce the inherent noise in simple individual measures such as Book to Price[5]. Both

5 Asness and Frazzini [ASN 13b] illustrate the high sensitivity of the Fama–French value-growth factor to simple variations in the definition of the HML (high minus low) metric such as the use of more recent prices.

long and short portfolios are market-capitalization weighted. In order to take into account implementation issues, and to avoid heavy sector and regional biases relatively to MSCI World index, additional constraints are imposed: maximum and minimum position size by individual stock (4.5% and 0.3%, respectively), relative sector and industry group weights (±20% and ±10%, respectively), and maximum relative currency exposure of ±10%. We also ensure that market neutrality, defined as an *ex ante* beta of 0, is achieved at the optimization stage.

The cross-asset trend-following factor is built from the application of directional momentum signal to bonds futures, credit default swaps (CDS) indices, equity index futures and foreign exchange futures and forwards. The strategy is long assets with positive trends, and short assets with negative trends. Following ample evidence in the academic literature, trends are assessed with simple signals by averaging the sign of past returns over 3 and 12 months lookback windows. Positions in individual contracts are risk-weighted, with risk budgets defined so that on average each asset class contributes equally to the overall risk of the factor.

Foreign Exchange (FX) value is another type of global macro strategy. It invests in a basket of G10 currencies. It compares current exchange rates with OECD PPP implied ones and is long undervalued currencies and short overvalued ones. Risk budgets depend on the distance from fair value: the cheaper (dearer) a currency is, the higher (more negative) its risk budget will be.

Finally, we also derive a diversified range of carry strategies[6]. Bonds carry invests 10-year bonds futures in a basket of developed economies. It goes long futures with above-median carry, and short futures with below-median carry. Carry is defined as the underlying yield in excess of short-term interest rate plus roll-down yield. Weights are proportional to the distance from the median: the further away from the median, the higher the absolute risk budget. Positions are scaled so that the portfolio remains duration neutral. FX carry is defined in a very similar way. It goes long futures or FX forwards with above-median carry, and short the ones with below-median carry. Carry is defined by short-term interest rates' differential between each country's currency and the US short-term interest rates. Risk budgets for each currency are proportional to the distance from the median: the further from the median, the higher the absolute risk budget. We separate developed markets (DM) and emerging markets (EM) FX carry strategies. Not doing so would result in a strategy that, on average, would be long EM currencies, and short DM currencies, which would extract an emerging market premium more than a pure FX carry. Credit carry invests in two pairs of investment grade and high-yield CDS indices covering Europe and North-America. It buys protection (short credit) on the

6 See [KOI 17] for a general analysis of carry strategies. For a specific introduction to the dividend and equity volatility carry strategies, see [BOU 13] and [SIM 14], respectively.

investment grade indices, and sells protection (long credit) on the high-yield indices. For each region, the ratio of investment grade to high yield indices is risk based in order to achieve market neutrality. Dividends carry invests in a synthetic constant 1-year maturity dividends future on the EuroStoxx 50. As EuroStoxx 50 dividends have annual maturities, it will go long the front (current year) and second (next year) contracts in proportions that keep the overall maturity of the portfolio at 1 year. In order to build a market-neutral portfolio, this position is hedged by short positions in EuroStoxx 50 futures with similar maturity. The ratio of EuroStoxx 50 futures to dividends futures is beta based. Volatility carry shorts (goes long) the front VIX futures when the VIX curve is in contango (backwardation), and simultaneously goes short (long) S&P 500 futures contracts in order to build a market-neutral portfolio. The ratio of S&P 500 futures to VIX futures is risk based.

12.3.2. *Empirical characteristics*

In Table 12.2, we report descriptive statistics for the various alternative risk premia over the full sample. Alternative risk premia have historically posted high risk-adjusted returns, usually at least on par or above long-term Sharpe ratios from traditional asset classes. Some risk premia exhibit negative skewness: this is the case for most carry strategies (bonds carry, FX carry and dividends carry), as well as for quality and size factors. In addition, all of them have positive excess kurtosis. In particular, credit carry and volatility carry risk premia, while exhibiting slightly positive skewness, have very high kurtosis of 13.59 and 9.03, respectively. This highlights the fact that most of the alternative risk premia may represent a compensation for bearing extreme risks. However, contrary to the theory developed in [LEM 17], alternative risk premia cannot be deemed as compensation for negative skewness only as it does not reflect evidence across a large set of strategies[7] and investors should probably be looking at additional complementary explanations such as macro factors as we show later on.

Figure 12.1 represents the cumulative excess returns of the alternative risk premia jointly with the cumulative returns due to the carry of the portfolio. Quite unsurprisingly, the carry component is a key driver of the long-term return of the vast majority of carry strategies, but also benefited trend following over the period, notably as the strategy has remained long asset classes such as fixed income during most of the period.

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7 Koijen *et al*. [KOI 17] also report that strategies post mixed results in terms of sign of skewness.

	Trend following	FX value	Bonds carry	Credit carry	DM FX carry	EM FX carry	Dividends carry	Volatility carry	Equity quality	Equity size	Equity momentum	Equity value
Excess return p.a.	7.7%	5.2%	7.1%	6.4%	4.2%	7.5%	2.7%	7.1%	2.2%	6.0%	4.2%	7.4%
Volatility	11.3%	10.6%	10.5%	12.3%	10.2%	12.7%	11.3%	12.7%	8.5%	10.2%	10.8%	10.5%
Sharpe ratio	0.69	0.48	0.68	0.52	0.41	0.59	0.24	0.56	0.26	0.59	0.38	0.70
Max. drawdown	13.2%	20.8%	17.4%	39.6%	33.7%	41.5%	29.2%	21.7%	24.5%	25.2%	26.7%	19.1%
Calmar ratio	0.59	0.25	0.41	0.16	0.12	0.18	0.09	0.33	0.09	0.24	0.16	0.39
Skewness	0.16	0.07	–0.09	0.77	–0.45	–0.36	–3.27	0.69	–0.20	–0.39	0.29	0.54
Kurtosis	3.23	3.37	4.43	13.59	3.64	4.53	20.21	9.03	5.13	6.49	5.26	4.31

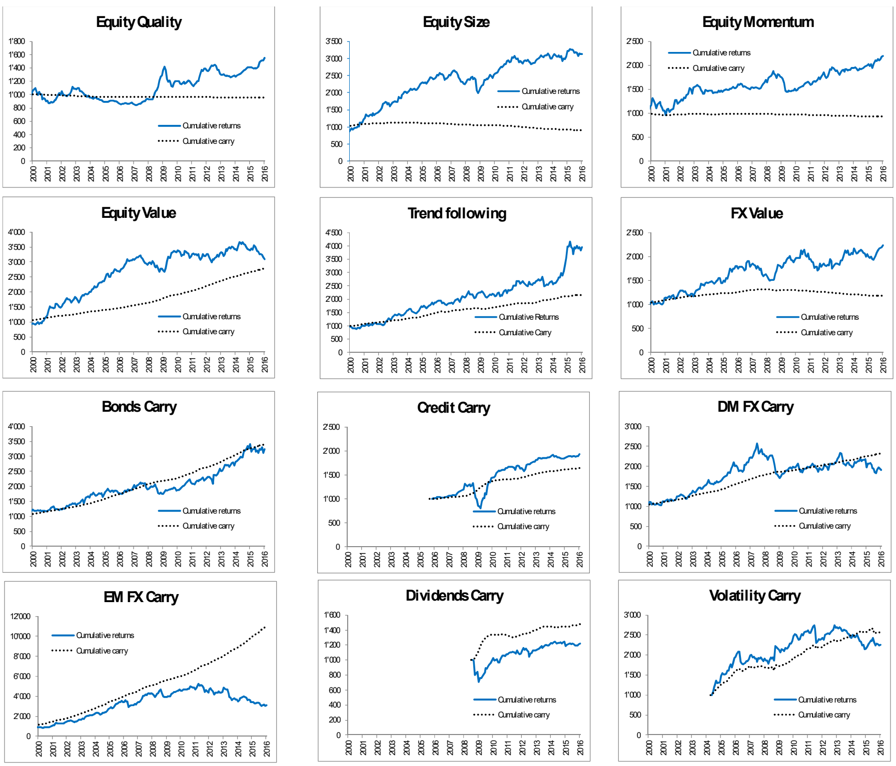
Note: The table displays the descriptive statistics for the different alternative risk premia based on monthly USD returns. The sample starts in January 1999 for most alternative risk premia with the exception of credit carry (November 2005), dividends carry (August 2008) and volatility carry (June 2004). The sample ends in December 2016 for all alternative risk premia.

Table 12.2. *Alternative risk premia descriptive statistics*

Component type	Growth nowcaster	Inflation nowcaster	Market stress nowcaster
# 1	Housing	Imported inflation	Liquidity
#2	Durable goods consumption	Input price inflation	Implied volatility
#3	Production expectations	Wage inflation	Credit spreads
# 4	Non-durable goods consumption	Supply-side inflation	
#5	Employment	Expected inflation	
#6	Financing conditions		
# 7	Investment perspectives		

Note: The table lists the typical components used in the growth, inflation and market stress nowcasters.

Table 12.3. *List of the components for each nowcasting indicator*



Note: The figure represents the cumulative excess returns (plain blue line) and the cumulative real carry (dotted black line) associated with each alternative risk premia.

Figure 12.1. *Alternative risk premia cumulative excess returns and cumulative carry*

In Table 12.3, we report historical correlations among alternative risk premia and between alternative risk premia and traditional asset classes (here measured by MSCI World All Country and Bloomberg Barclays Global Treasury indices). Correlations among alternative risk premia are low, with an average correlation across strategies of 0.03. Historical correlations between alternative risk premia and traditional risk premia have been low as well with average correlation to equities and bonds of 0.07 and 0.06, respectively.

Cross-correlations tend to be higher within the group of carry strategies, with the exception of bonds and volatility carry. In practice, most carry strategies tend to have higher correlation to equity markets in general, which shows that these risk premia probably share an exposure to a common equity-like factor. Cross-asset trend following and equity momentum are also positively correlated.

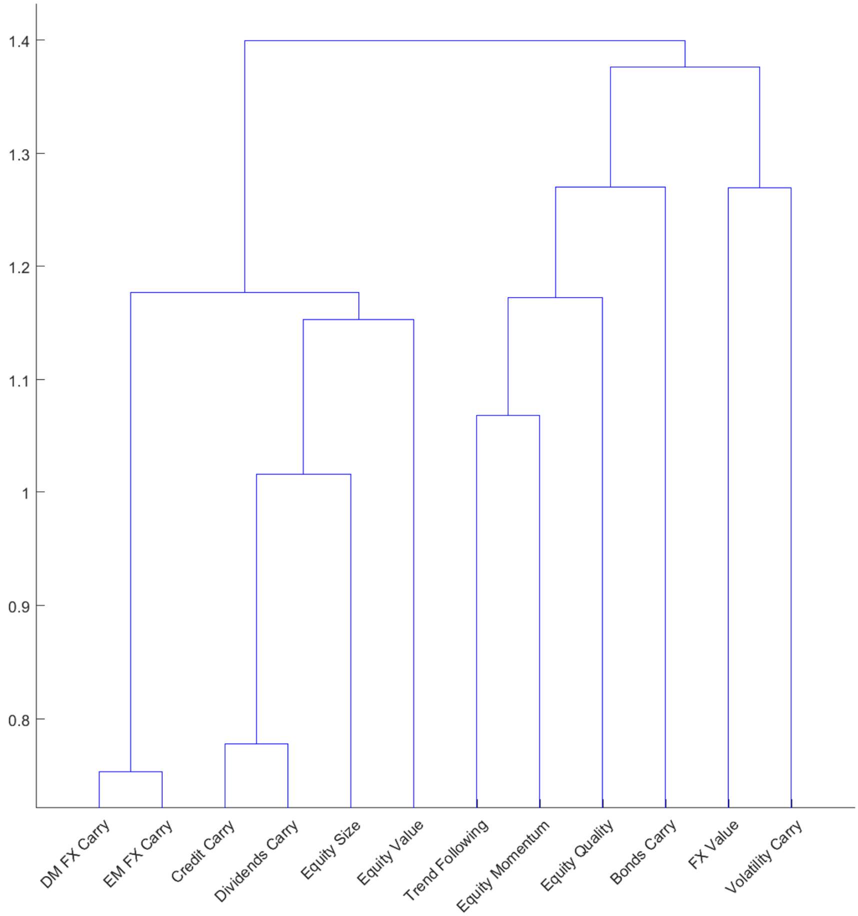
This does not come as a surprise, as they both exploit similar market regularities but one should note that they are based on very different investment universes and methodologies (the first one is based on time-series momentum, while the second uses a cross-sectional approach). The equity quality factor has the lowest correlation with other risk premia, averaging –0.15. This highlights its added value in terms of portfolio construction: while it has historically delivered a relatively low Sharpe ratio on a standalone basis, its diversification properties make it a very worthwhile addition to the portfolio.

In Figure 12.2, we display another way to visualize risk premia similarities through the representation of the dendrogram, which is based on the Euclidean distances of the correlation matrix. Two main groups of risk premia seem to emerge, with equity-correlated carry strategies on one side, and other alternative risk premia (typically with lower correlations to equities) on the other side. This grouping of strategies can also be seen when we compare the alternative risk premia across the economic regimes as we introduce it in section 12.4.

	Trend Following	FX Value	Bonds Carry	Credit Carry	DM FX Carry	EM FX Carry	Dividends Carry	Volatility Carry	Equity Quality	Equity Size	Equity Momentum	Equity Value	MSCI All Country World	Bloomberg Barclays Global Treasury
Trend Following	1.00	-0.18	0.15	-0.02	0.03	0.03	-0.12	0.06	0.09	0.06	0.30	-0.10	-0.10	0.40
FX Value	-0.18	1.00	0.00	-0.07	0.07	-0.01	-0.06	0.17	0.00	-0.04	-0.10	0.05	-0.18	0.03
Bonds Carry	0.15	0.00	1.00	-0.08	0.14	0.05	-0.07	0.03	-0.05	0.13	0.05	0.11	0.00	0.20
Credit Carry	-0.02	-0.07	-0.08	1.00	0.11	0.11	0.54	-0.07	-0.39	0.34	-0.12	0.14	0.33	-0.10
DM FX Carry	0.03	0.07	0.14	0.11	1.00	0.50	0.36	-0.01	-0.22	0.13	-0.05	0.16	0.46	-0.15
EM FX Carry	0.03	-0.01	0.05	0.11	0.50	1.00	0.20	0.16	-0.17	0.15	-0.07	0.18	0.42	-0.03
Dividends Carry	-0.12	-0.06	-0.07	0.54	0.36	0.20	1.00	-0.30	-0.39	0.30	-0.30	0.26	0.42	0.06
Volatility Carry	0.06	0.17	0.03	-0.07	-0.01	0.16	-0.30	1.00	0.01	-0.13	0.14	0.10	0.00	0.00
Equity Quality	0.09	0.00	-0.05	-0.39	-0.22	-0.17	-0.39	0.01	1.00	-0.32	0.28	-0.46	-0.36	0.12
Equity Size	0.06	-0.04	0.13	0.34	0.13	0.15	0.30	-0.13	-0.32	1.00	-0.02	0.25	0.05	0.05
Equity Momentum	0.30	-0.10	0.05	-0.12	-0.05	-0.07	-0.30	0.14	0.28	-0.02	1.00	-0.27	-0.22	0.14
Equity Value	-0.10	0.05	0.11	0.14	0.16	0.18	0.26	0.10	-0.46	0.25	-0.27	1.00	0.07	-0.04
MSCI All Country World	-0.10	-0.18	0.00	0.33	0.46	0.42	0.42	0.00	-0.36	0.05	-0.22	0.07	1.00	-0.25
Bloomberg Barclays Global Treasury	0.40	0.03	0.20	-0.10	-0.15	-0.03	0.06	0.00	0.12	0.05	0.14	-0.04	-0.25	1.00

Note: The table displays the correlation matrix for the group of alternative risk premia and two major traditional risk premia. Calculations are based on monthly USD returns. The sample starts in January 1999 with the exception of credit carry (November 2005), dividends carry (August 2008) and volatility carry (June 2004). The sample ends in December 2016 for all time series.

Table 12.4. *Alternative and traditional risk premia correlation matrix. For a color version of this table, see www.iste.co.uk/jurczenko/investing.zip*



Note: The figure displays the dendrogram representation of the correlation matrix of alternative risk premia (see Table 12.4). The alternative risk premia are arranged on the horizontal axis according to clusters while the vertical axis represents the Euclidean distance measure between the clusters.

Figure 12.2. *Alternative risk premia dendrogram*

	Trend following (%)	FX value (%)	Bonds carry (%)	Credit carry (%)	DM FX carry (%)	EM FX carry (%)	Dividends carry (%)	Volatility carry (%)	Equity quality (%)	Equity size (%)	Equity momentum (%)	Equity value (%)
Recession	58	60	63	48	45	58	50	48	70	58	53	53
Inflation	64	39	54	50	57	75	64	54	57	39	50	57
Market stress	57	65	70	67	43	43	46	60	78	48	74	35
Steady Growth	57	54	63	72	62	62	66	62	48	66	58	56
Full sample	58	55	63	62	56	61	60	58	56	59	58	53

Note: The table displays hit ratios of each alternative risk premia, both on the full sample and under each of the four macroeconomic regimes. Hit ratio represents the percentage of positive excess returns over cash. Calculations are based on monthly USD returns. The sample starts in January 1999 with the exception of credit carry (November 2005), dividends carry (August 2008) and volatility carry (June 2004). The sample ends in December 2016 for all time series.

Table 12.5. *Full sample and regime-conditional hit ratios*

12.4. Alternative risk premia and economic regimes: a first overview

We consider three major macroeconomic risks that affect markets: recession, inflation shocks and market stress[8]. Conversely, when none of these regimes materializes, the prevailing regime is assumed to be a steady growth one.

We therefore consider that the economic and financial environment consists of four regimes:

– Recession regime: In this configuration, economic growth sustains a severe shock and falls below its potential for an extended period. Excess production capacity generates a rise in unemployment and a significant decrease in consumption. Investments are reduced and the risk of default rises significantly. In practice, recessions are generally defined as sharp reduction in the global economy growth.

– Inflation shock *regime*[9]: For this type of period, inflationary pressures exceed the expectations of economic agents. This shock results from an imbalance between demand and supply, either coming from an overheating labor market (demand shock) or from a rapid and significant rise in the price of raw materials (supply shock). Periods of inflation shock are identified by comparing the difference between actual and expected[10] inflations. When actual inflation accelerates and exceeds expectations, the economy is considered to be in an inflation shock regime.

– *Market stress regime*: During such a regime, a sharp rise in risk aversion typical of this regime can occur following a period of exuberance in one or several

8 Ang [ANG 14] also considers three main major macro factors: growth, inflation and volatility.

9 We only consider inflation shocks to the upside, not to the downside. In recent years, lower inflation numbers have become an increasing source of concern for investors and officials, as emphasized by the Japanese experience of almost 20 years of very low inflation to deflation (a fall in consumer prices). As such long-lasting trends are generally fostered by structural factors (ageing, technological change, etc.), it is unclear whether they can affect the behavior of risk premia or not. Also, deflationary episodes are generally accompanied by very low growth and are thus partially captured by recessions. More globally, our analysis shows that the various frequencies associated to each economic regime are geographically robust (see Figure 12.1). They have been found to be consistent across a set of developed economies, such as Japan, the Eurozone or the U.K. Deflation impacts shorter term rates as central banks adapt their policy to the prevailing inflation environment, but its influence over returns in excess over cash is less clear.

10 Inflation forecasts are frequently measured through surveys (with economists or households) or derived from market-traded instruments such as inflation-linked bonds. Unfortunately, both types of measures are unavailable over long time periods and/or at a global level. Instead, we measure inflation expectations as one-year lagged inflation, meaning that we assume sticky inflation expectations.

markets and/or a specific event of limited duration. It has similar consequences to recessions on markets but it differentiates itself in two ways: first, such a regime is not related to economic fundamentals; second, its impact typically lasts a shorter period of time. Examples are September 11 attacks, August 2011 stock market falls, or China currency depreciation in August 2015. In general, market stress will be defined by a strong fall in risky assets, appreciation of safe assets, sharp increase in volatility or disruption in markets functioning and liquidity.

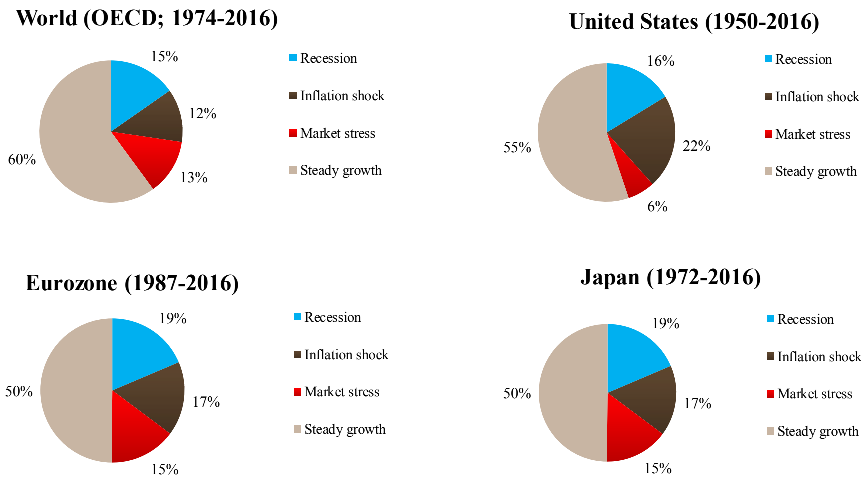
– *Steady growth regime*: In this regime, economic growth is close to or above potential, the unemployment rate is falling, lending to the private sector expanding and economic agents' sentiment is positive. Inflationary pressures are reined in by a restrictive monetary policy. By its very definition, this regime occurs when the other three regimes do not.

To estimate the various economic regimes, we mainly rely on an estimation strategy that employs conditionally Gaussian two-regime Markov-switching models. Two steps are needed to obtain an estimate for each regime dates: first, we estimate raw regimes using the Markov Switching models; then we rely on the following sequence: whenever a recession is diagnosed, then the prevailing regime is the recession one. When no recession is found for a given date and an inflation regime is estimated, then the dominant regime is inflation. If none of the above applies and a market stress regime is obtained from the estimation, then this period is a market stress one. The dates that would not fit in any of the previous three categories of events are steady growth periods. The raw regime estimation strategy unfolds as follows: the recession regime is the low[11] regime obtained when estimating the Markov switching model using a world activity index: the changes in the OECD economic activity index; the inflation surprise regime is the high regime obtained when estimating the Markov switching model using the difference between the OECD Consumer Price Index inflation and lagged inflation; finally, the market stress regime is the low regime obtained when running the estimation on the returns on the MSCI World index. The data frequency is monthly and the data set starts in January 1974 and ends in December 2016.

Figure 12.3 represents the associated unconditional long-term probabilities for each episode. For the world economy, recession periods represent roughly 15%. Around 12% of inflation shocks periods have occurred outside the recession periods. The frequency of market stress regimes is about 13%. As a by-product, the steady

11 For an introduction to Markov switching models, see [HAM 94]. In our empirical analysis, a regime is qualified a "low" regime (respectively "high") when the conditional expectation of the underlying macroeconomic variable is the lowest (respectively highest) of all regimes. For example, in the case of the economic activity index, the low regime will be the recession one, as recessions are the typical period over which such a time series is expected to reach its lowest values.

growth regime represents around 60% of occurrences. Figure 12.3 also displays similar estimation results in the case of different geographical zones, illustrating that the unconditional probabilities are pretty consistent across geographical zones and time periods.

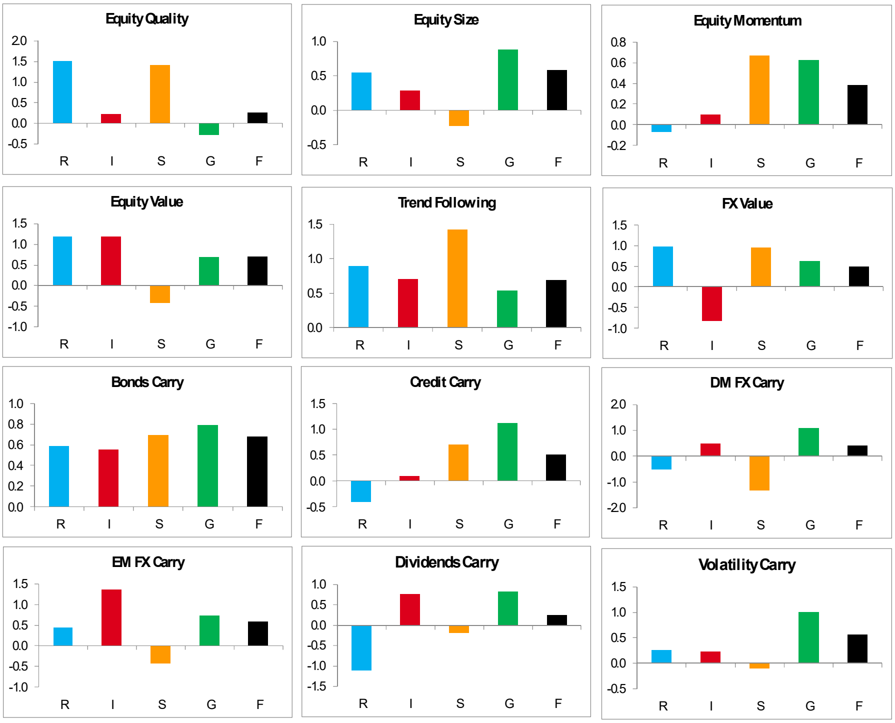


Note. The figure represents the unconditional probabilities associated with the different regimes for each geographical region. Recession, inflation shock and market stress regimes are estimated through Markov switching models applied to economic activity, inflation surprises and equity indices, respectively. Periods where none of these regimes are estimated to be prevalent are assumed to be steady-growth regime periods.

Figure 12.3. *Economic regime long-term probabilities. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

To illustrate the sensitivity of alternative risk premia to macroeconomic regimes, we represent in Figure 12.4 regime-conditional Sharpe ratios, and in Figure 12.5 regime-conditional excess Sharpe ratios, i.e. the difference between Sharpe ratios in each regime and the long-term (unconditional) Sharpe ratio[12]. Some strategies can be seen as being more “defensive”, such as trend following, FX value, bonds carry and the equity quality factor that tend to do better than average during periods of recession and market stress. On the other side of the spectrum, most carry strategies, as well as size and momentum equity factors tend to deliver lower than average Sharpe ratios during those regimes. However, as expected, they have historically delivered better than average results in steady growth periods.

12 For this calculation, we assume that volatility is unchanged across regimes. However, results are qualitatively unchanged when relaxing this hypothesis.

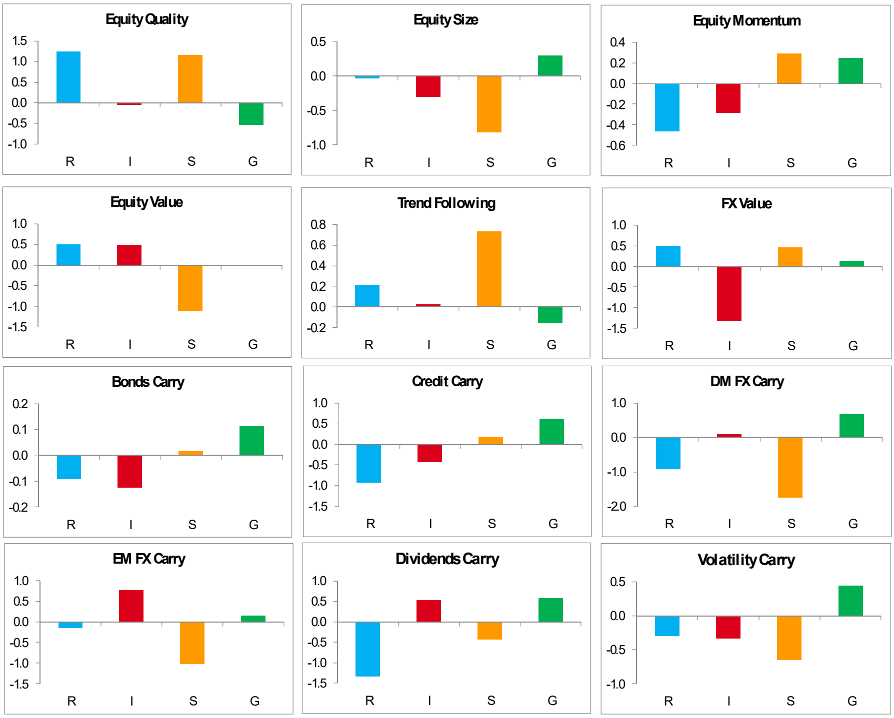


Note. The figure displays the Sharpe ratios for each of the four economic regimes (recession "R", inflation shock "I", market stress "S" and steady growth "G") and the full sample ("F"). For each regime, Sharpe ratios are defined as the annualized average regime-conditional excess returns divided by annualized volatility. We assume that volatility is unchanged across regimes.

Figure 12.4. *Regime-conditional Sharpe ratios. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

To further assess the performance of each alternative risk premia in each of the four macroeconomic regimes, we also measure their hit ratios under each regime, and in the full sample. We define hit ratio as the percentage of periods in the relevant regime where there is a positive excess returns over cash. Table 12.4 displays the full sample and regime-conditional hit ratios of each alternative risk premia. Once again, the more defensive strategies such as FX value, bonds carry and equity quality factor tend to have higher hit ratios than other risk premia during periods of recession and market stress. Equity momentum in particular has experienced the highest hit ratio in market stress periods. Meanwhile, carry strategies, as well as equity size factor, experienced higher hit ratios in steady growth periods. Emerging market FX carry, dividend carry and trend following had the highest hit ratios in inflation periods.

In section 12.5, we try to exploit those characteristics further by setting a macro-based asset allocation framework to the range of alternative risk premia.



Note: The figure displays the Sharpe ratios for each alternative risk premia in each of the four macroeconomic regimes (recession "R", inflation shock "I", market stress "S" and steady growth "G"), in excess of their full sample period Sharpe ratios. Sharpe ratios are defined as the annualized average regime-conditional excess returns divided by annualized volatility.

Figure 12.5. *Regime-conditional excess Sharpe ratios (in excess of full sample Sharpe ratios). For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

12.5. A macro risk-based asset allocation framework

In this section, we define and implement a process to allocate among alternative risk premia that incorporates, along other dimensions, each risk premium's sensitivities to the macro regimes. We start by describing the methodology and then apply it.

12.5.1. *Methodology*

As in the context of traditional portfolios, the allocation decision for a portfolio of alternative risk premia encompasses two dimensions:

– strategic allocation: Building a robust asset allocation for the long term, able to cope with the different economic and market regimes;

– dynamic (or tactical) allocation: Tilting the strategic allocation in order to improve portfolio's risk-adjusted performance over shorter time horizons.

Building a robust strategic allocation means finding the optimal risk budgets allocated to each alternative risk premia. Optimality can be defined in different ways. Rather than maximizing the full-sample Sharpe ratio – which would be the result of a standard mean-variance approach – we adopt an approach that focuses more on being robust across the various economic cycles ("all-weather"). In practice, we derive risk budgets by scoring each alternative risk premia across several dimensions that take into account their behavior under different macroeconomic regimes described in section 12.2 and more specific aspects of risk and practical implementation.

We start by a mapping the alternative risk premia to the different regimes described in section 12.2. We score alternative risk premia based on their average Sharpe ratio and hit ratios under the four regimes (as displayed in Figure 12.5 and Table 12.4). The goal is to favor the ones that have consistently delivered higher than average Sharpe ratios and hit ratios under each regime. This allows us to define baskets of alternative risk premia that we expect to perform well under each regime. These initial risk budgets are then adjusted for risk dimensions by penalizing the alternative risk premia with negative skewness, positive excess kurtosis, or who have exhibited large, positive downside correlations with traditional risk premia. The output of this mechanical scoring mechanism is then adjusted slightly in order to take into account the practicalities of implementation, notably expected liquidity and transaction costs[13]. Finally, regime-conditional scores are weighted by long-term probabilities of each regime in order to obtain the final risk budgeting. The resulting strategic risk allocation among alternative risk premia is displayed in Table 12.5. These risk budgets are translated into capital allocation using the latest available variance–covariance matrix at the end of each calendar month. The resulting portfolio is then scaled to 5% volatility.

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13 Such a final normative "overlay" is in general favored by practitioners and has been recently formalized as "flexible indeterminate factor-based asset allocation" by Blyth *et al.* [BLY 16].

	Risk budget (%)
Trend following	25.0
FX value	10.0
Bonds carry	8.0
Credit carry	3.0
DM FX carry	6.0
EM FX carry	6.0
Dividends carry	5.0
Volatility carry	7.0
Equity quality	7.5
Equity size	7.5
Equity momentum	7.5
Equity value	7.5

Note: The table displays the strategic allocation risk budgets. They are determined through a combination of quantitative and qualitative factors featuring the behavior of alternative risk premia in the various economic regimes, their individual extreme risks and the easiness of implementation/liquidity.

Table 12.5. *Strategic allocation to alternative risk premia*

The dynamic allocation consists of implementing active deviations from the strategic risk-budgets by incorporating two main dimensions: (1) the conditional probabilities of the economic regimes and (2) the carry associated with each of the alternative risk premia. The preliminary analysis in section 12.4 shows that both dimensions are important drivers of the performance of alternative risk premia.

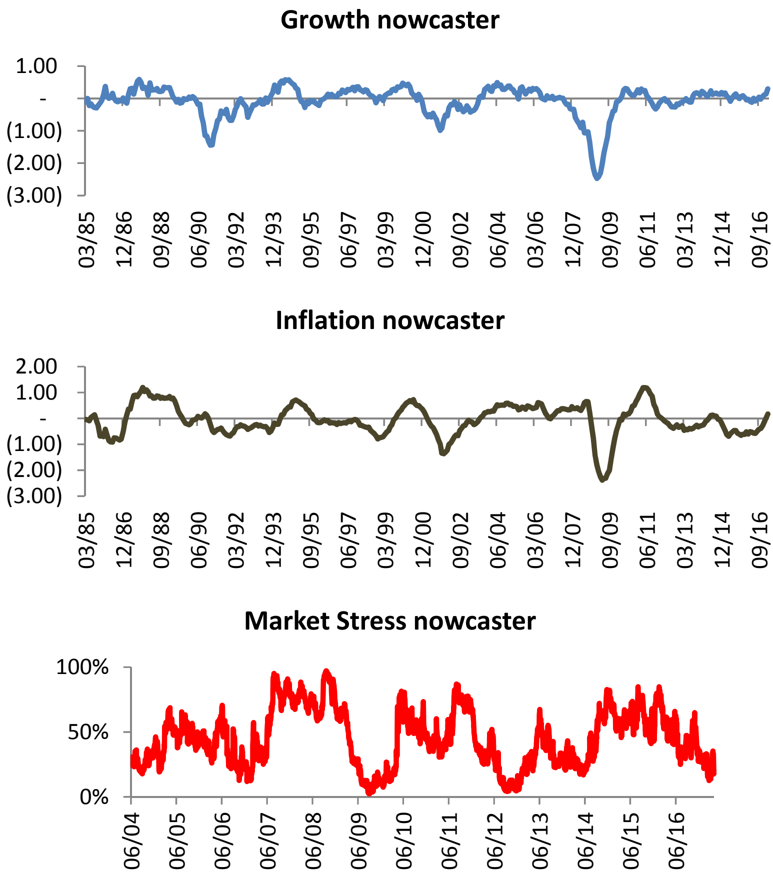
Regarding economic regimes, the analysis presented in section 12.4 is, however, of little practicality when it comes to asset allocation. The issue is that the information on regimes is usually available with a lag that inhibits its application for asset allocation purposes. For example, GDP figures that are necessary to date recessions per country are regularly published with a lag of 20 to 60 days. In addition, they are frequently revised afterward. A higher frequency and more rapidly available measure of these regimes must be constructed to be able to use this regime information with the necessary timeliness. It is the purpose of "nowcasting" indicators to solve these issues.

"Nowcasting" comes from the contraction of "now" and "forecasting" and is used to describe the practice of estimating current economic conditions. Nowcasting methodologies rely on hard data such as industrial production and soft data such as surveys to nowcast GDP growth. Recent academic research [BEB 15] suggests that nowcasters are not only more effective in tracking the business cycle but also in identifying its implication for financial markets dynamics and asset allocation. One of the very useful characteristics of nowcasters for backtesting strategies is that they can be designed as point-in-time indicators, that is as only using indicators as they were available at that moment in time and not how they appeared afterward due to lag in publication or *ex post* revisions[14]. For this study, we have developed three types of point-in-time nowcasters that are presented in the Appendix: a growth nowcaster, an inflation nowcaster and a market stress nowcaster. A graphical illustration of these indicators is provided in Figure 12.6.

In order to build our active risk-based portfolios, we start by estimating active returns stemming from both carry and nowcasters. Carry active returns are based on a time-series approach, where we compute z-scores comparing the current level to its history. Nowcasters' active returns are based on historical sensitivities of the alternative risk premia to the recession, inflation and market stress regimes and the current state of corresponding nowcasters[15], z-scored on a cross-sectional basis. We set the sensitivities by comparing each alternative risk premia's Sharpe ratios under different regimes on a cross-sectional basis. All carry and nowcaster indicators are point-in-time and only use information available at each rebalancing date.

Following Jurczenko and Teiletche [JUR 14], the z-scores stemming from the carry and nowcasters' indicators are translated into active returns. The combined active returns from carry and nowcasters is simply defined as the sum of the two sets of active returns. Active portfolio weights are computed by multiplying the active returns by the inverse of the alternative risk premia volatilities, and scaled by the ratio between the strategic portfolio's risk and its Sharpe ratio. Active allocations are scaled so as to deliver 2% tracking error on average, and capped at 4%.

14 Ignoring this latest feature can lead to severe biases in empirical backtesting of strategies, as shown by Ghysels *et al*. [GHY 12] for the predictability of bond returns.
15 The state associated with each nowcaster at any date is established on the basis of the current level of the nowcaster and its associated diffusion index based on the dynamics of the individual components. The states are calibrated to replicate the long-term probabilities of the economic regimes as displayed in Figure 12.3.



Note: The figure displays the time series evolution of the three nowcasting indicators used in our empirical analysis: the growth nowcaster (top), the inflation nowcaster (middle) and the market stress nowcaster (bottom). The methodology to the creation of each indicator is presented in the Appendix.

Figure 12.6. *Evolution of the nowcasting indicators*

12.5.2. *Empirical results*

The asset allocation methodology drawn in the previous section is backtested from January 2005 to December 2016. The period from January 1999 to December 2004 is used to initiate the model. The target allocations are recomputed at the end of each month, only using information that is available up to the previous market close.

Table 12.6 summarizes the performance statistics of the portfolio. The returns are net of transaction costs[16]. The first column shows the "strategic" portfolio, which is the portfolio where the (*ex ante*) risk budgets are based on the allocation policy displayed in Table 12.5. The second to fourth columns show the "dynamic" portfolios that incorporate active tilts, based on carry and nowcasters signals individually and in combination.

	Strategic	Dynamic		
		Carry signal only	Nowcasters signal only	Both signals combined
Annualized returns	10.0%	10.6%	11.1%	11.9%
Annualized volatility	5.6%	5.7%	5.6%	5.7%
Sharpe ratio	1.42	1.49	1.60	1.73
Maximum drawdown	9.7%	12.8%	8.1%	8.7%
Calmar ratio	0.81	0.66	1.11	1.13
Tracking error	–	2.0%	1.5%	2.2%
Information ratio	–	0.32	0.76	0.89

Note: The table displays descriptive statistics from four different simulations. "Strategic" represents the simulation based on a fixed strategic risk budgets as displayed in Table 12.5. "Carry", "nowcasters" and "combination" are simulations using the dynamic allocation process described in section 12.4, with expected returns estimated, respectively, with "carry" signal only, "nowcasters" signal only and a combination of both. Tracking error and information ratios are computed relative to the "strategic" simulation as benchmark. Calculations are based on USD monthly net returns of transaction costs. The sample starts in January 2005 and ends in December 2016 for all simulations.

Table 12.6. *Strategic versus dynamic allocation to alternative risk premia: risk and returns over the full sample*

16 Transaction costs hypothesis are as follows: Bonds futures 4 bps, CDS 20 bps, DM equity futures 4 bps, EM equity futures 15 bps, volatility futures 30 bps, G10 currencies 4 bps, EM currencies 15 bps, single stocks 10 bps.

All strategies have delivered high risk-adjusted returns, with Sharpe ratios ranging between 1.42 and 1.73[17]. The Strategic portfolio has greatly benefitted from diversification, with improved risk-adjusted returns relative to individual alternative risk premia over the same period, and low drawdown compared to the level of realized volatility. Dynamic allocation based on the individual signals has added value through improved returns for comparable risk levels, and even more so when using them in combination. The reason behind this incremental performance from the combination lies in their diversification properties. As displayed on Table 12.7, active returns from the dynamic signals have the interesting property of neither being correlated with the strategic portfolio (negative correlation of –0.08 for the allocation based on carry signals, and –0.20 for the one based on nowcasters), nor with one another (historical correlation of –0.3 between carry-based and nowcasters-based active returns). The resulting information ratios range from 0.32 to 0.89. This highlights the fact that, although a well-balanced allocation to various risk premia generated a significant portion of the returns, additional value can be extracted from dynamic allocation in realistic implementable strategies.

	Strategic	Carry active returns	Nowcasters active returns	Combination active returns
Strategic	1.00	–0.08	–0.20	–0.21
Carry – active returns	–0.08	1.00	–0.30	0.80
Nowcasters – active returns	–0.20	–0.30	1.00	0.28
Combination – active returns	–0.21	0.80	0.28	1.00

Note: The table displays the historical correlations between returns from the strategic portfolio simulation, and the active returns delivered by the “carry”, “nowcasters” and “combination” signals. Calculations are based on USD monthly returns net of transaction costs. The sample starts in January 2005 and ends in December 2016 for all simulations.

Table 12.7. *Correlations between strategic portfolio and dynamic portfolios active returns*

Table 12.8 displays the Sharpe ratios of the strategic and the dynamic portfolios in the different economic regimes. There is no significant difference between Sharpe ratios achieved in inflation or market stress regimes, but these are the two regimes with the least number of observations (23 and 15, respectively). The most dramatic improvement in Sharpe ratios compared to the strategic portfolio is observed during the recession regime, where the added value of nowcasters led to a Sharpe ratio improvement from 0.94 to 1.64. Although this effect is dominated by the behaviour observed during the Great Financial Crisis in 2008 and 2009, this shows how

17 The order of magnitude of strategic and dynamic portfolios Sharpe ratios is comparable to the results obtained in [CAR 14].

real-time identification of regimes can benefit even a well-diversified portfolio during extreme macroeconomic shocks. The Sharpe ratio is also improved in steady growth periods, which has historically been the most prevalent macroeconomic regime. During these periods, the dynamic portfolio combining nowcaster and carry signals delivered a 2.09 Sharpe ratio compared to 1.93 for the strategic portfolio. This improvement comes from both the nowcasters and carry strategies, and once again, the improvement from the combination is greater than that from the individual signals.

	Strategic	Dynamic		
		Carry signal only	Nowcasters signal only	Both signals combined
Recession	0.94	0.82	1.60	1.64
Inflation	1.42	1.50	1.35	1.44
Market stress	1.89	2.04	1.82	1.97
Steady growth	1.93	2.07	1.95	2.09

Note: The table displays the Sharpe ratio of the four simulations under different economic regimes. Calculations are based on USD monthly returns net of transaction costs. The sample starts in January 2005 and ends in December 2016 for all simulations.

Table 12.8. *Strategic versus dynamic allocation portfolios of alternative risk premia: Sharpe ratio by regime*

12.6. Conclusion

Alternative risk premia investing is garnering a growing interest from investors. While their individual behavior has been the subject of many studies, we have here investigated the less-frequently studied question of their allocation. This dimension has been largely overlooked both in the academic literature and by practitioners that frequently rely on the (static) ERC approach [MAI 10]. One of the issues with this approach is that it ignores the sensitivity of alternative risk premia to macroeconomic shocks.

In this chapter, we have presented evidence on the significant and differentiated reaction of a large range of cross-asset alternative risk premia in major economic and market regimes. Drawing on recent advances on active risk-based investing [JUR 14], we have designed a macro risk-based allocation methodology to distribute capital across alternative risk premia.

For this, we have started by defining a long-term strategic risk budget allocation that we have dynamically tilted based on two major types of signals: nowcasting indicators of macroeconomic regimes and the current carry of individual alternative risk premia. We have backtested the strategy in an out-of-sample setting over the period 2004–2016 for a diversified range of alternative risk premia strategies.

While usual caveats apply to our strategy, the application indicates that investors can enhance the results of static portfolios over the full economic cycle and particularly in bad times such as recessions. In further work, the empirical application could easily be extended by considering other types of signals, such as momentum or valuation.

12.7. Appendix: Nowcasting economic regimes

Nowcasting indicators have emerged over the past 10 years, essentially through the efforts of the research departments of various central banks. One of the first attempts to create a methodology to "nowcast" GDP growth in the United States using timely economic newsflow can be found in [EVA 05]. The Federal Reserve of Atlanta proposes an online nowcasting indicator for the US economy that follows the methodology presented in [HIG 14]. There has been well-nowcasting indicators developed for other economies: see, for example, Giannone *et al*. [GIA 08] in the case of the Eurozone, Mitchell [MIT 09] for the UK, or Ferrara and Marsilli [FER 14] for the world economy. Banbura *et al*. [BAN 12] provide an overview of the existing literature on nowcasting indicators.

Here, we develop three types of point-in-time nowcasters: a growth nowcaster, an inflation nowcaster and a market stress nowcaster. All of them are aggregations of a large spectrum of economic and market indicators that provide a broad view on a spectrum of various economies: mixing indicators both decreases the noise attached to individual data series and provides a broader take on complex phenomenon such as recessions as suggested in the academic literature following the seminal research from Stock and Watson [STO 02].

Our approach to building nowcasters unfolds as follows: each indicator is a combination of a limited number of components, each of which is a mixture of a shortlist of time-series. Say $x_t^{i,j}$ is the observation at time t of the ith time series incorporated in the jth component of a given nowcaster. C_t^j, the value of the jth component at time t, is then computed as follows:

$$C_t^j = \frac{1}{I_j}\sum_{i=1}^{I_j} x_t^{i,j} \quad [12.1]$$

where I_j is the number of time series used to build the jth component. The $x_t^{i,j}$ are scaled time series: the original time series can have different scales, such as rates of variation or headline indicators. Scaling every data series makes them comparable so that they can be summed as in equation [12.1]. Finally, the value for a given nowcaster N_t at time t is given by the following formula:

$$N_t = \frac{1}{I_N} \sum_{j=1}^{I_N} C_t^j \qquad [12.2]$$

where I_N is the number of components associated with the nowcasting indicator. As highlighted in equation [12.2], each component receives the same weight in the final indicator. Principal component analysis could have been used to find the optimal weight per data series given the history of the data set: it would, however, potentially prevent the model from capturing the signal of a recession that would not look like the recessions available in the estimation sample. Furthermore, this would introduce some estimation noise in the nowcasters. The equal-weight scheme that we use leaves each component free to contribute equally to the dynamics of the indicator.

To save space, the full list of the underlying data used to build the indicators is not presented here, but the table below provides a list of the types of component from which each nowcaster is made up of. In the case of the growth nowcaster, the list of the countries for which a nowcasting indicator is computed is the following: the United States, the UK, the Eurozone, Japan, Canada, Switzerland, Brazil, Russia, India, China, South Africa and Mexico. For the inflation nowcaster, emerging countries have been excluded as emerging inflation is probably more the reflection of food inflation and local currencies' evolutions. The more domestic bent of such factors are unlikely to affect the global course of assets. We aggregate the country level measures using proprietary weights that balance the economic significance of each economic zone alongside its significance for markets returns. Typically, the three zones with the largest weights will be the United States, the Eurozone and China. Finally, the market stress nowcaster has a global geographical scope and is an aggregation of various market indicators related to volatility and liquidity. The final output of each indicator is presented in Figure 12.6.

12.8. Bibliography

[AHM 12] AHMERKAMP J., GRANT J., KOSOWSKI R., Predictability in carry and momentum strategies across asset classes, SSRN working paper, 2012.

[ANG 04] ANG A., BEKAERT G., "How Regimes Affect Asset Allocation", *Financial Analysts Journal*, vol. 60, pp. 86–99, 2004.

[ANG 14] ANG A., *Asset Management - A Systematic Approach to Factor Investing*, Oxford University Press, New York, 2014.

[ASN 00] ASNESS C., FRIEDMAN J., KRAIL R., LIEW J., "Style timing: value versus growth", *Journal of Portfolio Management*, vol. 26, pp. 50–60, 2000.

[ASN 13a] ASNESS C., MOSKOWITZ T., PEDERSEN L., "Value and momentum everywhere", *Journal of Finance*, vol. 88, pp. 929–985, 2013.

[ASN 13b] ASNESS C., FRAZZINI A., "The devil in hml's details", *Journal of Portfolio Management*, vol. 39, pp. 49–68, 2013.

[BAL 15] BALTAS N., "Trend-Following, Risk-Parity and the Influence of Correlations?", in JURCZENKO E. (ed.), *Risk-Based and Factor Investing*, ISTE Press, London and Elsevier, Oxford, 2015.

[BAL 13] BALTAS N., KOSOWSKI R., Momentum strategies in futures markets and trend-following funds, SSRN working paper, 2013.

[BAN 12] BANBURA M., GIANNONE D., MODUGNO M. *et al*., "Nowcasting and the real-time data flow", *CEPR Discussion Papers n°9112*, 2012.

[BEB 15] BEBER A., BRANDT M., LUIZI M., "Distilling the Macroeconomic News Flow", *Journal of Financial Economics*, vol. 117, pp. 489–507, 2015.

[BLI 17] BLIN O., LEE J., TEILETCHE J., "Alternative risk premia investing: from theory to practice", *Unigestion Research Paper*, 2017.

[BLY 16] BLYTH S., SZIGETY M., XIA J., "Flexible Indeterminate Factor-Based Asset Allocation", *Journal of Portfolio Management*, vol. 42, pp. 79–93, 2016.

[BOU 13] BOURGOIS S., TOM E., Extracting the dividend risk premium, Credit Suisse Equity Derivatives Strategy, 2013.

[CAR 97] CARHART M., "On persistence in mutual fund performance", *Journal of Finance* vol. 52, pp. 57–82, 1997.

[CAR 14] CARHART M., CHEAH U.W., DE SANTIS G. *et al*., "Exotic beta revisited", *Financial Analysts Journal*, vol. 70, pp. 24–52, 2014.

[COC 11] COCHRANE J., "Presidential address: discount rates", *Journal of Finance*, vol. 66, pp. 1047-1108, 2011.

[COO 16] COOPER I., MITRACHE A., PRIESTLEY R., A global macroeconomic risk explanation for momentum and value, SSRN working paper, 2016.

[DAN 16] DANIEL K., MOSKOWITZ T., "Momentum crashes", *Journal of Financial Economics*, vol. 122, pp. 221–247, 2016.

[EBN 16] EBNER M., Risk and risk premia: a cross asset class analysis, SSRN working paper, 2016.

[EVA 05] EVANS M., Where are we now? real-time estimates of the macro economy, National Bureau of Economic Research working paper n°11064, 2005.

[FAM 93] FAMA E., FRENCH K., “Common risk factors in the returns on stocks and bonds”, *Journal of Financial Economics*, vol. 33, pp. 3–56, 1993.

[FER 14] FERRARA L., MARSILLI C., Nowcasting global economic growth: a factor augmented mixed-frequency approach, Bank of France working paper n°515, 2014.

[GIA 08] GIANNONE D., REICHLIN L., SMALL D., “Nowcasting: the real-time informational content of macroeconomic data”, *Journal of Monetary Economics*, vol. 55, pp. 665–676, 2008.

[GHY 12] GHYSELS E., HORAN C., MOENCH E., Forecasting through the rear-view mirror: data revisions and bond return predictability, Federal Reserve Bank of New York, Staff Report n°581, 2012.

[GNE 14] GNEDENKO B., YELNIK I., Dynamic risk allocation with carry, value and momentum, SSRN working paper, 2014.

[HAM 94] HAMILTON J., *Time Series Analysis*, Princeton University Press, Princeton, 1994.

[HAN 80] HANSEN L., HODRICK R.., “Forward exchange rates as optimal predictors of future spot rates: an econometric analysis”, *Journal of Political Economy*, vol. 88, pp. 829–853, 1980.

[HAR 15] HARVEY C.R., LIU Y., ZHU H., “... And the cross-section of expected returns”, *Review of Financial Studies*, vol. 29, pp. 5–68, 2015.

[HIG 14] HIGGINS P., GDPNow: a model for GDP nowcasting, Federal Reserve Bank of Atlanta working paper, 2014.

[HUR 13] HURST B., OOI Y., Pedersen L., “Demystifying managed futures,” *Journal of Investment Management*, vol. 11, pp. 42–58, 2013.

[JUR 14] JURCZENKO E., TEILETCHE J., Active risk-based investing, SSRN working paper, 2014.

[KOI 17] KOIJEN R., MOSKOWITZ T., PEDERSEN L. *et al*., “Carry”, *Journal of Financial Economics*, forthcoming 2017.

[KRI 21] KRITZMAN M., PAGE S., TURKINGTON D., “Regime shifts: implication for dynamic strategies”, *Financial Analysts Journal*, vol. 68, pp. 22–39, 2012.

[LEM 14] LEMPERIERE Y., DEREMBLE C., NGUYEN T. *et al*., “Two Centuries of Trend Following”, *Journal of Investment* Strategies, vol. 3, pp. 41–61, 2014.

[LEM 17] LEMPERIERE Y., DEREMBLE C., NGUYEN T. *et al*., “Risk premia: asymmetric tail risks and excess returns”, *Quantitative Finance*, vol. 17, pp. 1–14, 2017.

[MAI 10] MAILLARD S., RONCALLI T., TEILETCHE J., “The properties of equally weighted risk contribution portfolios”, *Journal of Portfolio Management*, vol. 36, pp. 60–70, 2010.

[MEE 83] MEESE R., ROGOFF K., “Empirical exchange rate models of the seventies: do they fit out of sample?”, *Journal of International Economics*, vol. 14, pp. 3–24, 1983.

[MIT 09] MITCHELL J., "Where are we now? The UK recession and nowcasting GDP growth using statistical models", *National Institute Economic Review*, vol. 209, pp. 60–69, 2009.

[MOS 12] MOSKOWITZ T., OOI Y., PEDERSEN L., "Time series momentum", *Journal of Financial Economics*, vol. 104, pp. 228–250, 2012.

[NOV 13] NOVY-MARX R., "The other side of value: the gross profitability premium", *Journal of Financial Economics*, vol. 108, pp. 1–28, 2013.

[PIO 00] PIOTROSKI J., "Value investing: the use of historical financial statement information to separate winners from losers", *Journal of Accounting Research*, vol. 38, pp. 1–41, 2000.

[RON 17] RONCALLI T., "Alternative risk premia: what do we know?", in JURCZENKO E. (ed.), *Factor Investing*, ISTE Press, London and Elsevier, Oxford 2017.

[SIM 14] SIMON D., CAMPASANO J., "The VIX futures basis: evidence and trading strategies", *Journal of Derivatives*, vol. 21, pp. 54–69, 2014.

[STO 02] STOCK J., WATSON M., "Forecasting using principal components from a large number of predictors", *Journal of the American Statistical Association*, vol. 97, pp. 1167–1179, 2002.

[WAN 10] WANG K., XU J., Time-varying momentum profitability, SSRN working paper, 2010.

13

Optimizing Cross-Asset Carry

The term "carry" has been primarily studied and explored within currency markets where, contrary to the uncovered interest rate parity, borrowing from a low interest rate country and investing in a high interest rate country has historically delivered positive and statistically significant returns. This chapter extends the notion of carry to different asset classes by looking at the futures markets of commodities, equity indices and government bonds. We explore the profitability of cross-sectional and time-series variants of the carry strategy within each asset class but most importantly we investigate the benefits of constructing a multiasset carry strategy after properly accounting for the covariance structure of the entire universe. Multiasset carry allocations benefit from the low correlation between asset-class specific carry portfolios and do not exhibit significant downside or volatility risk, which have been traditionally associated with the FX carry strategy.

13.1. Introduction

The term "carry" is generally associated with an FX trading strategy that borrows from a country with a low interest rate and invests in a country with a high interest rate, aiming to capitalize the rate differential as long as the FX rate does not exhibit any adverse move in the meantime, which wipes out any gains[1].

Historically, short-term FX movements have been unpredictable, hence rendering the FX carry trade a profitable strategy. This profitability constitutes a violation of the no-arbitrage condition of uncovered interest rate parity and the carry premium can only be justified as long as it constitutes compensation for some

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1 One can argue that the term carry relates to the "*cost of carry*", a term associated with commodities markets and the theory of "*normal backwardation*", introduced by Keynes [KEY 30]. However, we believe that "carry" has become popular in the investment community when associated with the FX markets.

systematic source of risk; otherwise, it should be related to mispricing. The academic evidence seems conflicting, but the most plausible explanations justify the premium as compensation for bearing currency or equity crash risk. We provide a more detailed review of the suggested explanations later in the chapter.

Generalizing the above concept and drawing motivation from Koijen *et al.* [KOI 17], we define "carry" as the return (or "yield") that an investor enjoys if all market conditions, including the asset's price, remain the same. In other words, carry measures the value appreciation that accrues to the owner of an asset if there is no expected or unexpected price change:

$$Return = \underbrace{\boldsymbol{Carry} + \boldsymbol{E}(price\ appreciation)}_{\boldsymbol{E}(Return)} + unexpected\ price\ shock \qquad [13.1]$$

Following from this equation, the estimation of carry becomes readily available and therefore requires no model assumptions[2]. Most importantly, it allows us to extend the concept of carry and explore its potential profitability across different asset classes: commodities, government bonds, equity indices and, obviously, FX. Our first objective is therefore to define and measure carry for each asset class and subsequently to document the performance of simple carry portfolios separately for each asset class.

Our second objective is to explore in detail the diversification benefits from constructing a multiasset carry portfolio and the added value of actively making use of the rich multiasset covariance structure. Historically, the vast academic work on FX carry has focused on simple cross-sectional (by ranking the currencies based on the Libor rate of the respective country) cash-neutral portfolios. Fewer papers have also looked at the time-series nature of the carry signals (that is the momentum of carry) and even fewer papers have actively looked at optimizing the allocation based on some portfolio optimization methodology. In all fairness, focusing on a single asset class (FX in this case) can possibly justify the employment of simple portfolio weighting schemes, as the members of a single asset class generally exhibit similar levels of volatility and stable correlations. If there is any breadth in the covariance structure, this is at a multiasset level. This is exactly what we are after: to construct risk-optimized multiasset carry portfolios.

The literature on carry is vastly dominated by studies that focus on the FX carry trade. Table 13.1 provides an overview of the recent academic activity. However, there is very little evidence on carry dynamics across multiple asset classes. The

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2 In a Bayesian framework, one can argue that carry represents the mean of the uninformed prior of expected returns. However, one can even support the idea of carry being the mean of the informative prior of expected returns.

only papers that exist – to our knowledge – are by Ahmercamp and Grant [AHM 13], Baz *et al.* [BAZ 15] and Koijen *et al.* [KOI 17]. Interestingly, none of these papers focus explicitly on the diversification potential of combining cross-sectional with time-series carry signals, as well as improving the diversification of the multiasset portfolio by taking into account the covariance structure. This is the literature gap that this chapter aims to fill.

The rest of the chapter is structured as follows. Section 13.2 discusses the concept of FX carry and section 13.3 describes the extension to the multiasset space. Section 13.4 contains details on our data set and provides diagnostics of the carry metrics across asset classes. Section 13.5 constitutes the core part of the empirical analysis and includes results for cross-sectional, time-series and optimized variants of carry. Section 13.6 explores the dependence of carry strategies on crash risk. Section 13.7 concludes the chapter.

	Universe	Cross-sectional	Time series	Optimized
[BUR 11]	**FX**		√	
[OLS 14]	**FX**	√		
[BAR 15]	**FX**	√	√	√
[DOS 15]	**FX**	√		
[BEK 16]	**FX**	√		
[ACK 16]	**FX**	√		√
[DAN 17]	**FX**	√	√	√
[AHM 13]	**Multiasset**		√	
[BAZ 15]	**Multiasset**	√	√	
[KOI 17]	**Multiasset**	√	√	
This chapter	**Multiasset**	√	√	√

Table 13.1. *Recent literature on carry*

13.2. The concept of FX carry

The concept of carry has been manifested in the foreign exchange markets where historically borrowing at the low interest rate country and investing at the high interest rate country has yielded a statistically strong and positive excess return. Is this positive return justified by asset pricing principles? Does investing in the higher interest rate country come at a higher risk to justify the existence of a premium or is the carry premium an artifact of market inefficiency? To answer these questions, we first take a short detour around the fundamental no-arbitrage concepts of the uncovered and covered interest rate parities.

The uncovered interest rate parity (UIRP) is a no-arbitrage principle that suggests that any interest rate differential between two countries should be completely offset by an adverse movement in the exchange rate. In particular, the low interest rate currency should be expected to appreciate so much as to render an investor indifferent between (1) investing in the domestic Libor market and (2) investing in an FX carry trade, i.e. borrowing in the domestic Libor market, to invest in the foreign – higher rate – market and converting back any gains at a future date. Put differently, if UIRP holds, then the FX carry trade should not generate any statistically significant positive returns in excess of the domestic Libor market.

Contrary to these theoretical predictions, overwhelming empirical evidence (see [HAN 80] and [ENG 96]) has shown that the UIRP does not always hold in practice, at least for short horizons. In particular, the short-term exchange rate movements appear to be unpredictable (FX rates behave like martingales), which renders the carry trade, on average, profitable. The strategy would only generate negative excess returns if the FX rate exhibits an adverse movement that would wipe out the interest rate differential.

In order to eliminate (or correct) the market inefficiency and reinstate the no-arbitrage principle one can hedge against, or "cover", any unfavorable FX movements with the use of a forward contract that locks the future FX rate at which any gains will be converted back into the local currency. For obvious semantic reasons, this is called the covered interest rate parity (CIRP). Based on the CIRP, the investor would now be indifferent between (i) investing in the domestic market and (ii) borrowing in the domestic market to invest in the foreign – higher rate – market and entering a forward contract to lock the future exchange rate.

If CIRP holds, which is indeed generally the case, then the above strategies should generate the same return, and therefore the forward exchange rate for a contract maturing at time $t+1$, denoted by F_{t}, is uniquely determined by the spot foreign exchange rate, S_{t} as follows:

$$CIRP \Leftrightarrow F_t = S_t \cdot \frac{1+r_t^{\$}}{1+r_t^{*}}, \qquad [13.2]$$

where $r_t^{\$}$ denotes the prevailing at time-*t* domestic (USD) Libor rate and r_t^{*} denotes the respective foreign rate.

If both UIRP and CIRP hold, then it becomes obvious that the forward price becomes an unbiased predictor[3] of the futures stock price. This is referred to as the *forward rate unbiasedness hypothesis*:

$$\begin{Bmatrix} UIRP \\ CIRP \end{Bmatrix} \Leftrightarrow F_t = \mathbf{E}_t(S_T) \qquad [13.3]$$

However, as already mentioned, the UIRP does not empirically hold, in which case the above hypothesis does not hold either. As a result, the prevailing forward price is a biased predictor of the future spot exchange rate. The bias effectively represents the risk premium that the FX carry trade is trying to capitalize [FAM 84, LUS 11][4].

As to what is driving the risk premium associated with the FX carry trade, there has been a considerable debate in academic literature. The fact that FX carry has historically delivered superior risk-adjusted returns at the expense of a relatively sizeable negative skewness can effectively justify the positive returns as compensation for bearing currency crash risk [BRU 08, RAF 12, JUR 14, FAR 16]. This risk has been associated with funding liquidity risk [BRU 08, BRU 09], FX volatility risk [BHA 07, MEN 12], consumption growth risk [LUS 07] or even a “peso problem” [BUR 11][5]. The cyclicality of the carry trade has also been related to the equity market, hence justifying the premium as compensation for bearing equity downside risk [DOB 14, LET 14]. Adding to the debate, Bekaert and Panayotov [BEK 16] and Daniel *et al*. [DAN 17] challenge these crash-based explanations.

To summarize, the FX carry trade generally aims to capitalize on the empirical failure of the UIRP by borrowing from countries with lower interest rates and investing in countries with higher interest rates. In other words, a carry strategy for a USD investor would generally overweight countries with large interest rate differential $r_t^* - r_t^\$$ and, respectively, underweight countries with low (if not negative) interest rate differential.

Following the above, the interest rate differential is of critical importance in deciding the allocation in an FX carry trade. The crucial step that will allow us to extend the notion of carry to other asset classes is to depart from the interest rate

3 The expectation is under the physical probability measure, $\mathbb{P}$.

4 The “risk premium” should not be confused with the so-called “forward premium”, which is the difference between the spot exchange rate and the forward rate.

5 The “*peso problem*” explains the situation under which financial markets might appear inefficient and flawed, but in reality they could just incorporate an unprecedented and very low probability event that may simply have not yet occurred. Based on Sill [SIL 00], the term is often attributed to Nobel laureate Milton Friedman following his commentary on the Mexican peso/US Dollar exchange rate movement during the 1970s.

differential, which is an FX-specific metric of carry, to an asset class free definition. To achieve this, we start from equation [13.2] and solve for the rate differential:

$$r_t^* - r_t^\$ = \left(1 + r_t^\$\right) \cdot \frac{S_t - F_t}{F_t} \qquad [13.4]$$

Notice that the factor $\left(1 + r_t^\$\right)$ is just a proportionality factor, common across all foreign currencies, which represents the value of $1 at time $t+1$. As a result, the above equation allows us to generate trading signals for a carry strategy by looking directly at the term structure of futures prices. For instance, a country with a positive interest rate differential would have a futures curve in backwardation, and conversely a country with a negative interest rate differential would have a futures curve in contango. These statements set a clear path in extending the concept of carry to other asset classes outside FX, given that we can simply generate carry signals by looking at the respective futures markets. Section 13.3 explains these dynamics.

13.3. Extending the idea across asset classes

Following the detailed discussion of the FX carry dynamics, we can now formally define carry across multiple asset classes by observing directly the behavior of the respective futures/forward markets:

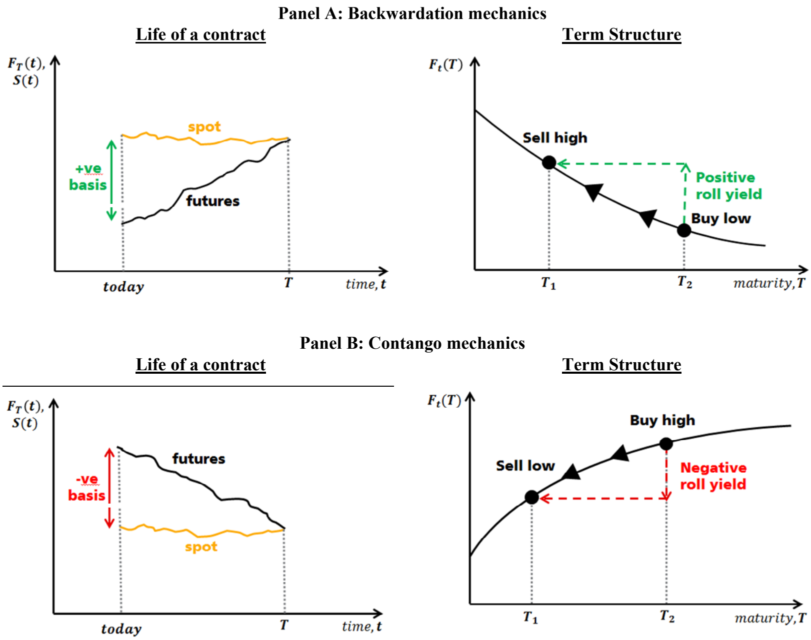
– Assets that exhibit a term structure of futures in *backwardation* should generate a *positive roll yield*, and therefore a positive excess return when market conditions remain unchanged. These assets should therefore be generally *overweighted* in a carry portfolio.

– Assets that exhibit a term structure of futures in *contango* should generate a *negative roll yield* and therefore a negative excess return when market conditions remain unchanged. These assets should therefore be generally *underweighted* in a carry portfolio.

Panels A and B of Figure 13.1 illustrate the above dynamics. Notice that when the market conditions remain unchanged, the term structure does not move at all and therefore the entirety of asset return is the roll yield.

The generic carry strategy of overweighting assets with the strongest backwardation and underweighting (or even going short; we will return to this point later on) assets with the strongest contango would therefore extract whatever "yield" each asset of any asset class is willing to pay the investor for holding it. In order to comprehend exactly the nature of this yield for each asset class, we start from equation [13.4] that is FX-specific and define carry, C_t, as the right-hand side of this equation (ignoring the proportionality factor that is common across assets), in line with Koijen *et al.* [KOI 17]:

$$C_t = \frac{S_t - F_t}{F_t} \qquad [13.5]$$



NOTE. The figure presents the carry dynamics for an asset in backwardation (panel A) or in contango (panel B) as long as the conditions do not change.

Figure 13.1. *Carry dynamics when the spot price does not change. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

Evidently, carry is just the slope of the futures curve. Using the arbitrage-free definition of the futures price per asset class and substituting it in the above equation, we can deduce what carry represents across the different asset classes.

Table 13.2 contains the arbitrage-free future price per asset class, as well as the value of carry based on equation [13.5] after substituting out F_t. The last column of the table explains in detail the type of yield that we can extract from each asset class:

– for FX markets, the investor receives (or pays, if negative) the interest rate of the foreign country in excess of the financing cost, which is obviously the domestic (USD) interest rate;

– for equity index markets, the investor receives the expected future dividend yield in excess of the financing cost;

– for commodity markets, the investor receives the convenience yield in excess of any storage and financing costs;

– for government bonds the investor receives two components of return: (i) the yield to maturity in excess of the financing cost (this is the so-called "term premium" [FAM 93]) and (ii) the "roll-down" of the bond across the yield curve as this approaches maturity.

Asset class	Futures price ($\boldsymbol{T-t=1\ year}$)	Carry	Carry interpretation
FX	$F_t = S_t \cdot \frac{1+r_t}{1+r_t^*}$ r_t^*: foreign risk-free rate	$C_t \propto r_t^* - r_t$	Capitalize the foreign risk-free rate *in excess of the financing cost*
Equity indices	$F_t = S_t \cdot (1 + r_t - q_t)$ q_t: dividend yield	$C_t \propto q_t - r_t$	Capitalize the expected dividend yield *in excess of the financing cost*
Commodities	$F_t = S_t \cdot (1 + r_t + c_t - y_t)$ c_t: storage costs y_t: convenience yield	$C_t \propto (y_t - c_t) - r_t$	Capitalize the convenience yield net of the storage costs, *in excess of the financing cost*
Government bonds	$F_t = \frac{1+r_t}{(1+y_t^{10Y})^{10}}$ y_t^{9Y}, y_t^{10Y}: 9-yr, 10-yr ZCB yield	$C_t \propto y_t^{10Y} - r_t$ $-D_{mod} \cdot (y_t^{9Y} - y_t^{10Y})$ D_{mod}: *modified duration*	Capitalize (i) the yield to maturity and (ii) the roll-down of the bond across the yield curve, *in excess of the financing cost*

NOTE: Interpretation of carry from [KOI 17].

Table 13.2. *The notion of carry across asset classes*

Given these interpretations one might wonder why a carry strategy can generate positive excess returns. What is the underlying economic rationale? Is there any risk that we are compensated for? In what follows we provide some narrative that can guide us:

– FX: *Why should higher yielding currencies outperform lower yielding currencies?*

We have already elaborated on the reasons why the FX carry trade has historically exhibited positive returns higher Libor rates are generally associated with rising inflation, funding liquidity concerns, or consumption growth risk, which render the higher yielding currencies generally more vulnerable, hence justifying the positive FX carry. For relevant academic literature, see the summary earlier in section 13.2.

– Commodities: *What can justify the convenience yield (in excess of any storage costs) that an investor earns from investing in a backwardated commodity?*

Keynes's [KEY 30] theory of "normal backwardation" suggests that commodity producers take short futures positions in order to hedge against price drops and therefore pay a premium to an investor that offers this insurance and takes a long position in the futures contract; this positive premium comes in the form of the carry premium. An alternative explanation of backwardation that is inventory related suggests that storing a commodity (given the costs) should compensate the holder with a positive return (hence "convenience" yield) in periods of short supply; the underlying risk here being that these short supply shocks can turn out to be temporary. Contrary to Keynes's point, one can argue that commodity consumers take long futures positions in order to hedge against unexpected future price surges; in this scenario, they should pay a premium to the investor that offers the insurance and takes a short position, in which case contango arises. In any case, roll yield has been documented as an important driver of commodity returns [ERB 06, ERB 16, GOR 06, YAN 13, GOR 13, BHA 15].

– Government bonds: *What are the risks of investing in a long-term bond, when the yield curve is upward sloping (hence, the futures curve in backwardation)?*

Holding a bond up to maturity should compensate an investor with the yield-to-maturity in excess of the risk-free rate (short-term end of the yield curve); this is effectively the term spread or the slope of the yield curve, which is one of the main drivers of bond returns [FAM 87, CAM 91, FAM 93]. Yield curves are typically upward sloping and therefore the term spread is positive in order to compensate long-term bond investors for potential illiquidity risk (longer dated bonds being less liquid than shorter dated bonds), tightening monetary policy risk and inflation risk (increasing rates in expectation of higher inflation) or some broader macroeconomic risk.

– Equity indices: *Why should an index with higher expected dividend yield outperform an index with lower expected dividend yield?*

If the equity carry strategy turns out to be profitable and if it constitutes compensation for systematic risk, then surely equity indices with higher expected dividend yield must be fundamentally riskier. This discussion resembles equity value investing, where dividend yields have historically been good predictors of stock returns [FAM 88, CAM 88, ANG 07]. Put differently, the profitability of equity carry can be related to the equity value premium [FAM 93]. However, as is very nicely illustrated by Koijen *et al*. [KOI 17], a typical value strategy would use realized (hence backward-looking) dividend yield data; instead, an equity carry strategy focuses on the forward-looking – risk-neutral – expectation of future dividend yields as implied by market dynamics and therefore by the slopes of equity index futures curves.

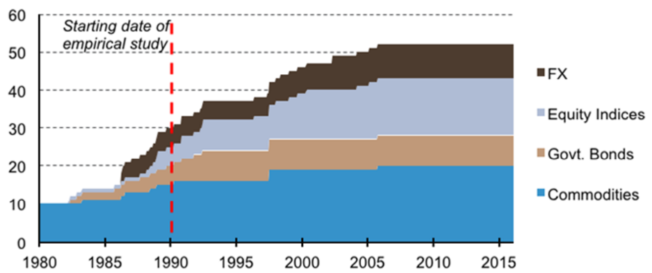
13.4. Data and carry diagnostics

Our empirical focus is on the construction of carry strategies using a broad universe of assets across asset classes. The purpose of this section is to describe our investable universe, to explain how we estimate carry for each asset class and to provide some elementary data diagnostics before we proceed with the core part of our empirical analysis in section 13.4.1.

13.4.1. *The universe of assets and asset classes*

For the purpose of our empirical analysis, we collect futures data from Bloomberg for a large cross-section of 52 assets: 20 commodities (constituents of the Bloomberg Commodity index excluding the precious metals, i.e. gold and silver), eight 10-year government bonds, nine FX rates (G10 pairs against USD) and 15 equity country indices (see Table 13.3 for the entire cross-section). We specifically use the roll-adjusted front futures contracts in order to do any back-testing analysis.

Figure 13.2 presents the number of assets per asset class over time. Our simulations start in January 1990, as this is the first time that we can estimate carry signals for at least five assets per asset class. The sample period ends in January 2016.



NOTE. Data collected from Bloomberg.

Figure 13.2. *Number of assets per asset class. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

		Exc. Returns (ann.)		Carry (ann.)	
Asset	**Starting Month**	**Geom. Mean**	**Volatility**	**Geom. Mean**	**St. Dev.**
Commodities					
Natural Gas	Feb-91	-13.6	57.6	-16.7	8.1
Heating Oil	May-87	7.7	35.9	5.6	6.1
Unl. Gasoline	Aug-06	0.3	35.5	6.6	3.6
WTI Crude	Jan-84	3.3	35.8	1.9	4.5
Brent Crude	Apr-89	6.7	33.9	3.4	4.0
Sugar #11	Dec-70	-6.4	41.8	-2.7	4.7
Live Cattle	Dec-70	4.4	17.7	0.7	3.2
Lean Hogs	Mar-87	-5.3	24.6	-6.6	5.4
Coffee C	Jun-73	-2.5	39.5	-2.5	4.9
Cotton #2	Dec-70	-1.1	26.3	-2.1	4.3
Soybeans	Jan-71	1.9	28.2	-1.7	2.9
Corn	Dec-70	-4.1	26.0	-8.8	2.3
Wheat	Dec-70	-4.1	27.8	-5.2	3.2
Soybean Oil	Dec-70	2.3	32.7	-0.5	4.9
Soybean Meal	Dec-70	6.1	30.7	-0.3	3.7
Kansas Wheat	Dec-70	0.7	26.1	-2.1	2.9
Copper	Oct-89	2.9	25.7	2.9	2.1
Aluminium	May-98	-7.0	19.8	-4.2	0.9
Nickel	May-98	3.4	36.4	1.5	1.6
Zinc	May-98	-2.4	27.1	-3.6	0.7
FX					
EUR	Jan-99	-0.8	10.4	-0.4	0.5
JPY	Jan-89	-2.2	11.0	-3.0	1.0
GBP	Jan-89	0.7	9.4	4.9	1.9
AUD	Feb-87	2.9	11.5	1.8	0.5
CAD	Jan-89	0.0	7.8	0.9	0.7
CHF	Jan-89	0.1	11.3	-2.3	1.4
NZD	Jun-97	2.4	13.4	1.3	0.2
SEK	Jun-02	1.2	11.9	0.1	0.3
NOK	Jun-02	0.5	12.0	0.5	0.2

		Exc. Returns (ann.)		Carry (ann.)	
Asset	**Starting Month**	**Geom. Mean**	**Volatility**	**Geom. Mean**	**St. Dev.**
Equity Indices					
US - S&P500	Apr-83	5.9	15.0	-1.9	0.7
Canada - S&P TSX 60	Oct-01	5.0	13.2	-0.1	0.4
Germany - DAX	Jun-92	4.2	21.5	-2.6	0.5
UK - FTSE 100	Feb-89	2.4	14.6	-1.5	0.9
Korea - Kospi 200	Mar-97	6.4	34.0	-1.9	0.8
Japan - Nikkei 225	Jul-89	-2.9	21.9	-0.9	0.8
Australia - ASX 200	Mar-01	2.6	13.5	-0.3	0.4
HK - Hang Seng	Feb-93	6.8	26.5	0.4	0.6
Spain - IBEX 35	May-93	5.6	21.2	0.3	0.9
Switzerland - SMI	Oct-99	2.1	14.4	1.1	0.5
France - CAC 40	Nov-89	2.6	19.2	-0.6	1.1
Norway - OBX	Apr-06	2.8	21.8	-2.6	0.3
Netherlands - AEX 25	Dec-89	5.4	19.8	0.0	0.6
Italy - MTSE MIB	Feb-05	-2.3	21.4	2.0	0.3
Sweden - OMX 30	Dec-05	5.4	17.9	1.8	0.4
Government 10-year Bonds					
US T-Note	Jun-82	4.9	6.9	3.0	0.5
Australian GB	Oct-87	0.5	1.2	0.9	0.5
Canadian GB	Oct-89	4.0	6.0	2.1	0.5
German Bund	Dec-90	4.4	5.2	2.0	0.5
Japanese GB	Nov-85	3.4	5.1	1.9	0.4
UK Gilt	Dec-82	2.8	7.5	0.4	0.7
Swiss GB	Jul-92	4.0	4.6	2.1	0.3
New Zealand GB	Nov-91	0.3	1.0	0.6	0.5

NOTE: Sample period ends in January 2016.

Table 13.3. *Descriptive statistics: average realized returns versus average carry*

13.4.2. *Measuring carry across asset classes*

Table 13.2 in the previous section explains the nature of carry for each asset class in terms of expected yield. However, in order to actually construct carry portfolios we need to estimate the level of carry for each asset of each asset class at the end of each rebalancing period (monthly for the purpose of our analysis) using data readily available at the time.

The level of carry is estimated as the slope of the futures/forward curve for each asset in the spirit of equation [13.5]. In order to measure the slope of the curve one can use either spot and front futures data or front and back futures data. Due to the various idiosyncrasies of each asset class, as well as due to data availability, we use an asset class specific metric for the slope of the future curve. Further technical details on these calculations are given in section 13.8. Briefly, for FX markets we use spot and 1-month forward data, for equity indices and commodities we use data for the first two (i.e. front and back) futures contracts and seasonally adjust the carry metrics, and for government bonds we use zero coupon bond data in order to calculate spot and synthetic 1-month future prices of a 10-year bond.

Table 13.3 presents annualized average excess returns and volatility for each asset as well as the level of annualized average carry and its respective standard deviation. The table conveniently reports as well the starting date for each asset (this is the first month that we can generate a carry signal for each asset).

Figure 13.3 presents the median carry for each asset class at the end of each month over the entire sample period in order to identify asset class shifts between contango and backwardation over time.

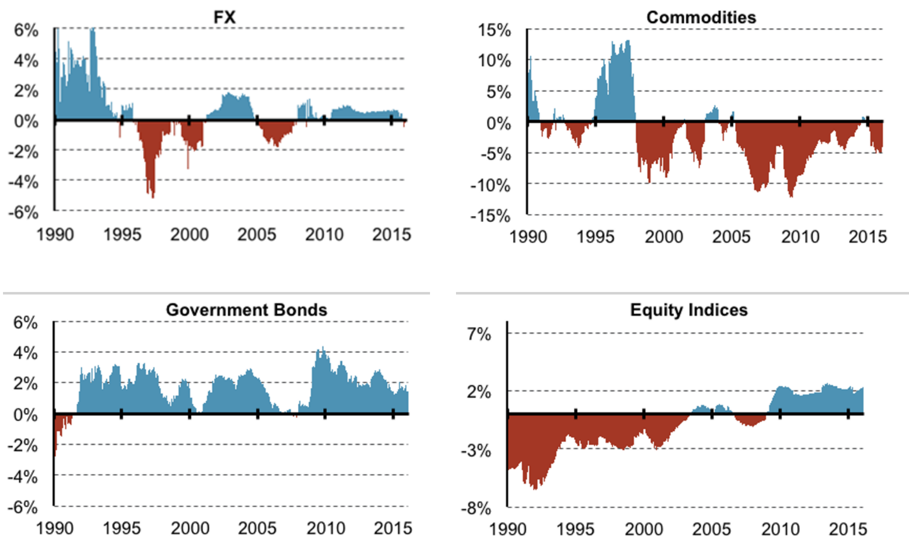
Here are some emerging patterns that are worth mentioning:

– FX: Being the asset class most familiar to us on the carry landscape, typical patterns emerge. JPY and CHF have generally been the currencies with negative carry (so in contango), whereas AUD and NZD have been the currencies with positive carry. On a time-series basis, the median carry effectively tracks the overall strength of USD; positive when Libor US rates are generally lower than the rest of the G10 currencies and negative otherwise.

– Commodities: Historically, the storage of commodities has provided (positive) convenience yield at times of supply squeezes. However, after the introduction of the Commodity Futures Modernization Act (CFMA) 2000 the universe of commodities has started behaving more like a universe of financial assets, hence turning into contango during the most recent decade.

– Government bonds: Being invested in long-term government bonds has historically generated positive excess returns. Upward sloping yield curves correspond to downward sloping bond futures curves and therefore all bonds in our universe (and the universe as a whole) have been mostly in backwardation during our sample period. For the bond markets to turn to contango, the yield curves should invert, which is generally the case prior and during economic recessions, as also witnessed in the time-series plot; notice the zero or negative median carry during the early 1990s recession, after the dot-com bubble in 2001 and during the global financial crisis of 2007–2009.

– Equity indices: While historically in contango, as the dividend yield used to be lower than the Libor rate, equity indices have turned into backwardation following the recent financial crisis, as rates have fallen to extremely low levels (if not zero) and therefore an equity investor benefits from the dividend yield if the conditions remain unchanged. This transition between contango and backwardation is obvious from the time-series plot in Figure 13.3.



NOTE: The figure presents the median carry across all assets of each asset class at the end of each month, January 1990–January 2016.

Figure 13.3. *Carry in the time series of assets (1990M01–2016M01). For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

13.5. Constructing carry portfolios

With all the pre-work in place, we can now proceed with constructing carry portfolios within each asset class, but most importantly across all asset classes in a multiasset framework.

In constructing carry portfolios, we explore three different weighting schemes[6]:

1) Cross-sectional ("XS") carry: The *relative strength of the carry* of each asset compared to all other assets in the same asset class is used in order to construct a balanced long-short portfolio in terms of notional exposure.

2) Times-series ("TS")/absolute carry: The *sign of the carry* of each asset is used to determine the type of position (long or short) in order to construct a portfolio with explicit directional tilts; net long when the majority of assets are in backwardation, and net short when in contango.

3) Optimized ("OPT") Carry: Both the *relative strength* and the *sign of the carry* are used in order to determine the type (long or short) as well as the gross exposure for each asset. Most importantly, the optimized carry portfolio additionally accounts for the *covariance structure* between assets and asset classes in a way that risk allocation is optimized.

As already noted, the XS form of carry is definitely the most familiar to the investment community due to FX carry. The TS form has been less of a focus in academic works, whereas the optimized form has never been addressed in a multiasset framework. Our objective is to discuss all three forms, but eventually focus on the optimized portfolio.

13.5.1. *Cross-sectional carry*

Let N_t denote the number of available contracts at time t. Using the latest carry estimate for each asset, C_t^i, with $i = 1, \dots, N_t$, we rank all assets within the same asset class in increasing order (i.e. high ranks are associated with high-carry assets). We then assign linear weights to the assets, which are proportional to the demeaned ranks[7] (the average rank of N_t assets equals $\frac{N_t+1}{2}$):

$$\widehat{w}_t^{XS,i} = rank\left(C_t^i\right) - \frac{N_t+1}{2} \quad [13.6]$$

6 One can draw parallels between cross-sectional and time-series forms of carry and the equivalent forms for momentum: cross-sectional [JEG 93, JEG 01] and time series [MOS 12].
7 For further details on this weighting scheme, please also see [ASN 13] and [BAL 14].

Evidently, assets with higher (either positive or negative) levels of carry relative to the rest of the universe will bear larger gross weights; this is one way that the relative strength of the signals translates into the XS weighting scheme. Obviously, the XS weights are symmetrical around zero, and in order to normalize them so to make no use of leverage (gross exposure of 100%), we simply rescale them by $\sum_{j=1}^{N_t}\left|\widehat{w}_t^{XS,j}\right|$, so the final weights are:

$$w_t^{XS,i} = \frac{\widehat{w}_t^{XS,i}}{\sum_{j=1}^{N_t}\left|\widehat{w}_t^{XS,j}\right|} \qquad [13.7]$$

The weight symmetry results in zero net exposure, $\sum_{j=1}^{N_t} w_t^{XS,j} = 0$. Koijen *et al.* [KOI 17] use the same weighting scheme, with the only difference being that their level of gross exposure is fixed at 200% (sum of positive weights to 100% and sum of negative weights to –100%).

Table 13.4 presents various performance statistics for XS carry portfolios for each asset class. Broadly speaking, all asset classes generate positive excess returns with Sharpe ratios ranging from 0.19 for commodities to 0.85 for government bonds. The statistical significance of average returns is strongest for bonds (at 1% confidence), as the bonds with steeper yield curves have outperformed the bonds with less steep, if not inverted, yield curves. Equity XS carry has also generated significant excess returns (at 5% confidence), albeit with more volatility. Quite surprisingly, FX and commodities have been the asset classes where their XS carry returns, even though positive over the sample period, do not exhibit strong statistical significance (FX carry is just off the 10% threshold of statistical significance).

Focusing on higher moments, FX carry exhibits a large negative skewness (–0.77), which is consistent with the literature, followed by commodities and bonds that also have a small, though possibly insignificant negative skewness. However, in line with Koijen *et al.* [KOI 17], the equity XS carry strategy exhibits positive skewness, which can cast doubt on a crash/downside risk explanation of multiasset XS carry. We return to this point with a detailed analysis at a later stage, in section 13.6.

Next, we explore the diversification benefits from pulling together all XS carry portfolios, in order to construct a multiasset XS portfolio. As reported in Table 13.4, there is little correlation between these portfolios, which, on the one hand, means that building a unified framework that explains the XS carry patterns across all asset classes might be a challenging task but, on the other hand, it means that blending the different asset classes in a multiasset portfolio can deliver superior returns.

	FX	Commodities	Govt. bonds	Equity indices
Average excess return (%)	1.36	1.83	1.63***	3.09**
Annualized volatility (%)	4.39	9.59	1.93	6.43
Skewness	–0.77	–0.19	–0.04	0.80
Kurtosis	4.87	3.48	4.18	7.39
Maximum drawdown (%)	15.80	26.28	5.15	18.23
Sharpe ratio (annualized)	0.31	0.19	0.85	0.48
Sortino ratio (annualized)	0.43	0.28	1.42	0.83
Calmar ratio	0.08	0.05	0.31	0.16
Monthly turnover (%)	19.44	18.48	19.02	15.87
Correlation matrix:				
– FX	1.00			
– Commodities	0.01	1.00		
– Government bonds	0.06	–0.10	1.00	
– Equity indices	0.12	0.00	0.20	1.00

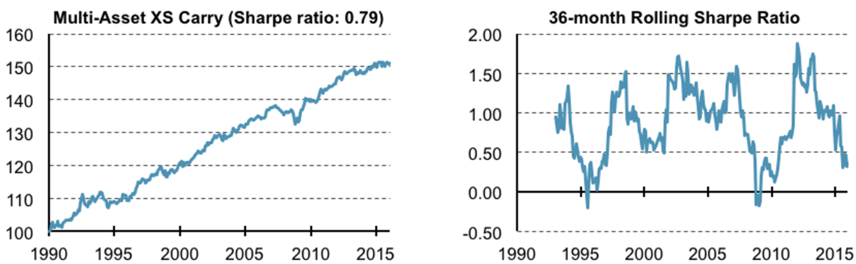
NOTE: The table presents performance statistics for cross-sectional (XS) demeaned-rank weighted carry strategies within each asset class (FX, commodities, government bonds and equity indices) as well as the correlations between each other. The statistical significance of the average return is indicated with *, ** and *** for 1, 5 and 10% confidence levels, using White [WHI 80] standard errors. The Sortino ratio is defined as the annualized excess return divided by downside volatility and the Calmar ratio is defined as the annualized geometric return divided by the maximum drawdown. The sample period is January 1990–January 2016.

Table 13.4. *Performance statistics for XS carry strategies across asset classes*

The fact that XS portfolios have rather different volatilities – this is due to the nature of the respective asset classes – justifies the use of a risk-based scheme for the construction of the multiasset portfolio. To keep things simple, we suggest combining XS portfolios on an inverse-volatility basis. The multiasset portfolio is rebalanced on a monthly basis using volatilities estimated using a 100-day rolling window of data. The cumulative returns of the portfolio as well as its 36-month rolling Sharpe ratio are presented in Figure 13.4. Performance statistics are reported in Table 13.5, including a levered version of the strategy that targets a volatility of 7%.

The multiasset XS carry strategy delivers statistically strong (at 1% confidence) average excess returns, generating a Sharpe ratio of 0.79, albeit at a negative skewness of –0.44 (in line with [KOI 17]) and with excess kurtosis. The portfolio volatility is 2.04% annualized, which is the result of the inverse-volatility scheme that we have employed, as well as of the low correlation between XS carry portfolios across the asset classes. For this reason, the volatility-targeted version of the strategy, which generates similar performance statistics, requires an average leverage of 4x, so to achieve the required 7% level of volatility.

In unreported results (available upon request), we find that all XS strategies (across asset classes and at the multiasset level) exhibit very low betas against various passive broad market indices (MSCI World Index, Bloomberg Commodity Index, JPMorgan Aggregate Bond Index and Trade-weighted USD). This market neutrality is largely driven by the cash-neutral nature of XS strategies. Importantly enough, the betas of the multiasset portfolio across all these market indices are largely shrunk toward zero. This finding highlights the diversification benefits of the multiasset XS carry portfolio.



NOTE. The figure presents cumulative monthly returns for the cross-sectional (XS) multiasset carry portfolio as well as its 36-month rolling Sharpe ratio. The multiasset portfolio is constructed as the inverse-volatility weighted portfolio of four each asset XS demeaned-rank weighted portfolios across FX, commodities, government bonds and equity indices. The portfolio is rebalanced monthly and the volatilities are estimated using a 100-day window. The sample period is January 1990–January 2016.

Figure 13.4. *Multiasset cross-sectional carry (unlevered). For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

	Unlevered	Levered – 7% target
Average excess return (%)	1.60***	5.88***
Annualized volatility (%)	2.04	7.30
Skewness	–0.44	–0.37
Kurtosis	4.99	4.86
Maximum drawdown (%)	4.19	18.61
Sharpe ratio (annualized)	0.79	0.81
Sortino ratio (annualized)	1.25	1.31
Calmar ratio	0.38	0.31
Monthly turnover (%)	21.83	23.92
Average leverage	1×	4.0×
25th–75th percentiles	1×–1×	3.2×–4.5×

NOTE: The table presents performance statistics for the cross-sectional (XS) multiasset carry portfolio both on unlevered basis as well as on levered basis, assuming 7% target volatility. The multiasset portfolio is constructed as the inverse-volatility weighted portfolio of four each asset XS demeaned-rank weighted portfolios across FX, commodities, government bonds and equity indices. The portfolio is rebalanced monthly, the volatility target for the levered strategy is also applied on a monthly basis and all volatilities are estimated using a 100-day window. The statistical significance of the average return is indicated with *, ** and *** for 1, 5 and 10% confidence levels, using White [WHI 80] standard errors. The Sortino ratio is defined as the annualized excess return divided by downside volatility and the Calmar ratio as the annualized geometric return divided by the maximum drawdown. In the estimation of the turnover, the absolute change in portfolio weights is normalized by the total gross exposure of the strategy in the beginning of the period. The sample period is January 1990–January 2016.

Table 13.5. *Performance statistics for multiasset XS carry strategies*

13.5.2. *Time-series carry*

Instead of focusing on the relative strength of the carry signals, one can construct a time-series carry (TS) strategy, by simply focusing on the sign of the carry of each asset. The TS form of the strategy would then assume a long position on assets with a positive carry (that is, assets in backwardation) and a short position on assets with a negative carry (that is, assets in contango), and assign equal gross weights across all assets (one can think of it as the "*momentum of carry*"):

$$w_t^{TS,i} = \frac{sign\left(c_t^i\right)}{N_t} \qquad [13.8]$$

Contrary to the XS form, the TS variant (i) is not taking into account the relative strength of the carry metrics, but only their sign and (ii) is not a cash-neutral strategy, $\sum_{j=1}^{N_t} w_t^{TS,j} \neq 0$ (notice, however, that we maintain the 100% gross exposure as in the XS variant for comparability). Instead, the TS has explicit directional tilts and is net long (short) when the majority of assets are in backwardation (contango). The net exposure of the strategy for each asset class roughly tracks the median carry of each asset class that was presented Figure 13.3.

Before proceeding with the presentation of our TS results, we should note that an alternative scheme to the equal gross weights ($1/N_t$) would be to use inverse-volatility gross weights. Given that we first construct portfolios for each asset class separately (before aggregating the asset classes to a multiasset portfolio), we can argue that the volatilities of the assets in the same asset class are, in practice, rather close and therefore the two weighting schemes (equal weights and inverse-volatility weights) will be numerically similar (see also Table 13.3)[8]. In unreported results, we conducted this analysis and obtained very similar results to those reported below.

Table 13.6 presents various performance statistics for TS carry portfolios for each asset class. Similar to the XS analysis, all asset classes generate positive excess returns with Sharpe ratios ranging from 0.10 for commodities to 0.88 for government bonds; this constitutes evidence that the level and sign of carry experience some degree of positive serial dependence. The statistical significance of average returns is again strongest for bonds (at 1% confidence). Interestingly enough, given the popularity of the XS nature of the FX carry, its TS form appears to generate even larger and statistically stronger returns (at 1% confidence). Equity indices and commodities, though generating positive returns over the sample period, fail to exhibit any statistical significance.

As far as the skewness of the strategies is concerned, it is only the FX carry that still exhibits large negative skewness (–0.58). All other asset classes generate either close to symmetrical return distribution or positive skewness, with the equity TS strategy exhibiting again (as in the XS case) the strongest positive skewness (0.70). As in the XS case, this evidence can cast doubt on a crash/downside risk explanation of multiasset TS carry. We will return to this point at a later stage in section 13.6.

Table 13.6 also reports the rank correlation of monthly returns between the TS carry strategies and the respective XS carry strategies for each asset class. Broadly speaking, the two forms of strategies share common features and the correlations range from 0.30 for equity indices to 0.68 for government bonds. Quite expectedly, when the carry signals are symmetrically distributed around zero, a TS strategy

8 One can contrast this to a time-series strategy that is constructed using all assets from all asset classes, like the default time-series momentum strategy of Moskowitz *et al.* [MOS 12]. In such an environment the use of inverse-volatility gross weights is obviously mandatory. For further information, see [BAL 15].

would very much resemble an XS strategy. Baz *et al.* [BAZ 15] and Goyal and Jegadeesh [GOY 15] offer an interesting discussion on XS versus TS dynamics.

	FX	Commodities	Govt. bonds	Equity indices
Average excess return (%)	3.02***	0.98	2.62***	2.74
Annualized volatility (%)	5.25	9.87	2.99	12.00
Skewness	–0.58	0.10	–0.01	0.70
Kurtosis	4.45	4.40	3.23	5.26
Maximum drawdown (%)	14.50	40.21	7.91	61.94
Sharpe Ratio (annualized)	0.57	0.10	0.88	0.23
Sortino Ratio (annualized)	0.85	0.15	1.51	0.37
Calmar ratio	0.20	0.01	0.33	0.03
Monthly turnover (%)	8.99	12.22	6.27	8.72
Rank correlation with XS	0.51	0.56	0.68	0.30
Correlation matrix:				
– FX	1.00			
– Commodities	–0.16	1.00		
– Government bonds	–0.00	0.11	1.00	
– Equity indices	0.09	–0.03	0.01	1.00

NOTE: The table presents performance statistics for time-series (TS) equal-gross weighted carry strategies within each asset class (FX, commodities, government bonds and equity indices). The statistical significance of the average return is indicated with *, ** and *** for 1, 5 and 10% confidence levels, using White [WHI 80] standard errors. The Sortino ratio is defined as the annualized excess return divided by downside volatility and the Calmar ratio as the annualized geometric return divided by the maximum drawdown. The table also reports the return rank correlation of the strategies with the respective XS strategies for the same asset class. The sample period is January 1990–January 2016.

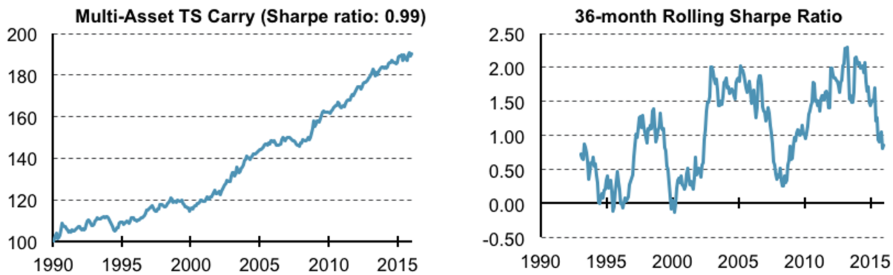
Table 13.6. *Performance statistics for TS carry strategies across asset classes*

We next combine the four TS carry portfolios into a multiasset portfolio using inverse-volatility weights (monthly rebalancing using 100-day volatility estimates). Figure 13.5 presents the cumulative returns and the rolling Sharpe ratio of the multiasset TS portfolio; Table 13.7 reports several performance statistics both for the unlevered strategy as well as for a levered version of the strategy that targets a volatility of 7%.

The multiasset TS carry strategy delivers a superior return profile compared to all asset class TS portfolios. The average excess return is statistically strong (at 1% confidence) and the Sharpe ratio is 0.99 for our sample period. Most importantly, the multiasset TS carry portfolio is positively skewed (as opposed to its XS variant), and the kurtosis is just slightly higher than 3. This tail behavior could be due to the diversification coming from the different asset classes as well as due to the occasional active (net long or net short) tilts of each asset class TS portfolio.

Due to the occasional directional tilts, the multiasset TS carry strategy exhibits an annualized volatility of 2.60%, which is, as expected, higher than that of its XS variant that maintains a more balanced profile (2.04% volatility from Table 13.5). As a result, the TS carry strategy requires an average leverage of 3.3x to achieve the required 7% level of volatility.

In unreported results (available upon request), we look at the betas of all TS strategies against various passive broad market indices (MSCI World Index, Bloomberg Commodity Index, JPMorgan Aggregate Bond Index and Trade-weighted USD). Contrary to XS strategies which are generally market-neutral, TS strategies exhibit relatively larger betas, even though not large in value. However, the multiasset TS portfolio exhibits rather small betas against the various markets. The diversification benefits of the multiasset class framework are again clearly exposed.



NOTE: The figure presents cumulative monthly returns for the time-series (TS) multiasset carry portfolio as well as its 36-month rolling Sharpe ratio. The multiasset portfolio is constructed as the inverse-volatility weighted portfolio of four each asset TS equal-gross weighted portfolios across FX, commodities, government bonds and equity indices. The portfolio is rebalanced monthly and the volatilities are estimated using a 100-day window. The sample period is January 1990–January 2016.

Figure 13.5. *Multiasset time-series carry (unlevered)*

	Unlevered	Levered – 7% target
Average excess return (%)	2.57***	8.14***
Annualized volatility (%)	2.60	7.89
Skewness	0.18	–0.06
Kurtosis	3.78	2.92
Maximum drawdown (%)	6.40	18.36
Sharpe ratio (annualized)	0.99	1.03
Sortino ratio (annualized)	1.79	1.85
Calmar ratio	0.40	0.44
Monthly turnover (%)	12.16	14.85
Average leverage	1×	3.3×
25th–75th percentiles	1×–1×	2.8×–3.9×

NOTES: The table presents performance statistics for the time-series (TS) multiasset carry portfolio both on unlevered basis as well as on levered basis, assuming 7% target volatility. The multiasset portfolio is constructed as the inverse-volatility weighted portfolio of four each asset TS equal-gross weighted portfolios across FX, commodities, government bonds, and equity indices. The portfolio is rebalanced monthly, the volatility target for the levered strategy is also applied on a monthly basis and all volatilities are estimated using a 100-day window. The statistical significance of the average return is indicated with *, ** and *** for 1%, 5% and 10% confidence levels, using White [WHI 80] standard errors. The Sortino ratio is defined as the annualized excess return divided by downside volatility and the Calmar ratio is defined as the annualized geometric return divided by the maximum drawdown. In the estimation of the turnover, the absolute change in portfolio weights is normalized by the total gross exposure of the strategy. The sample period is January 1990 to January 2016.

Table 13.7. *Performance statistics for multiasset TS carry strategies*

13.5.3. *The relationship between XS and TS carry strategies*

Analysis so far has shown that carry strategies, both in their XS and TS form, generate positive excess returns across all asset classes. The correlations between asset class portfolios are small, hence benefiting their multiasset combination. Table 13.8 summarizes the overall rank correlation structure between XS and TS carry strategies across asset classes and also at the multiasset class level.

	Cross-sectional carry				
Time-series carry	Commodities	Govt. bonds	FX	Equity indices	Multiasset
Commodities	0.56	0.06	–0.10	0.10	0.31
Govt. bonds	–0.12	0.68	–0.02	0.11	0.30
FX	0.06	–0.02	0.51	0.07	0.30
Equity indices	0.04	0.02	0.02	0.30	0.21
Multiasset	0.27	0.38	0.22	0.28	0.61

NOTE: The table presents the rank correlation between XS and TS carry strategies. The estimation uses monthly returns series and the sample period is from January 1990 to January 2016.

Table 13.8. *Return rank correlation between XS and TS carry strategies*

Broadly speaking, the correlation estimates are not extreme, which leads us to our ultimate objective in this chapter. It is one thing to benefit from diversification potential across asset classes, but it is a different thing to – additionally – benefit from the diversification potential of balanced (i.e. XS) and active (i.e. TS) strategies[9]. In other words, next we explore whether there is any return and/or diversification benefit from combining cross-sectional and time-series carry signals across all asset classes. Figure 13.6 presents a 36-month rolling rank correlation between our multiasset XS and TS carry strategies and appears to answer the question in an affirmative sense. The next section (section 13.5.4) focuses on the dynamics of combining XS and TS signals, while additionally optimizing the overall portfolio risk by actively making use of the rich cross-asset covariance structure.

NOTE: The figure presents the 36-month rolling rank correlation between XS and TS multiasset carry strategies. The sample period is from January 1990 to January 2016.

Figure 13.6. *36-month rolling rank correlation between XS and TS carry strategies*

9 To a certain extent, one can draw parallels with an investor that holds an equity long-only portfolio and seeks performance improvement from incorporating market-neutral long-short alternative beta strategies.

13.5.4. *Optimized carry*

In constructing a carry portfolio, the academic literature seems to have completely ignored the fact that its constituents have a proper covariance structure, which could be theoretically used to optimize portfolio risk and return. The only three exceptions are the very recent papers by Barroso and Santa-Clara [BAR 15], Ackermann *et al.* [ACK 16] and Daniel *et al.* [DAN 17], which highlight the benefits of portfolio optimization but only for FX carry portfolios. However, if there is any benefit from building optimized portfolios one would expect this benefit to be magnified for a multiasset universe, as it is characterized by a much richer and more dynamic covariance structure at the intra-asset-class and most importantly at the interasset class level. Following the above discussion, we consider this chapter to be the first attempt in the literature to explore optimized multiasset carry portfolios.

In constructing a multiasset portfolio, we generally have two broad options[10]:

– *Two-step approach*: First construct a portfolio for each asset class and then combine these portfolios to generate the multiasset portfolio. This has been the process that we have followed so far for the XS and TS strategies.

– *One-step approach*: Construct a portfolio across all assets in one step using all assets from all asset classes. It is of critical importance to notice that this approach must certify that the assets from each asset class are somehow "equally" treated in risk-return terms. A counterexample will help understanding this: think of a XS portfolio that ranks all the assets from different classes based on their carry metric. This procedure is flawed, unless the carry metric of each asset class is accordingly adjusted (e.g. scaled by asset volatility) to allow for cross-sectional comparison.

In order to construct our optimized multiasset portfolio, we expect a greater diversification benefit from using the one-step approach which assumes the full 52×52 covariance structure of all assets (even though we do acknowledge that this comes with more estimation error and potentially more turnover), than using the two-step approach, in which case the covariance structure is shrunk to the 4×4 covariance structure of the asset class portfolios[11]. For this reason, we proceed with the one-step approach; next, we discuss the portfolio optimization methodology.

10 For an interesting discussion on a relevant topic see [FIT 16].

11 On a technical note, if each asset class follows a CAPM-like single factor structure, then the two approaches would result in very similar allocations.

Jessop *et al.* [JES 13] show how risk-parity (RP)[12] allocation can be extended by introducing (i) expected returns and (ii) long and short positions. The findings of this report have been applied to a multiasset trend-following portfolio by Baltas [BAL 15]. Using the same principles, we next present the steps to the long-short risk-budgeting (RB) *weighting scheme* that we use for the multiasset optimized carry. This can be also considered as an extension to the Bruder and Roncalli [BRU 12] RB framework.

In the absence of any model of expected returns (we will relax this shortly), we suggest applying the RP principles and allocate equal amount of risk across the four asset classes; so each asset class should contribute 25% of the overall portfolio volatility. This 25% risk contribution of each asset class is equally allocated across all the constituents of the asset class. To achieve this in one step, we simply extend RP to RB with each asset i contributing $25\%/N_t^i$ amount of risk, where N_t^i denotes the number of assets that belong in the same asset class as asset i at time t:

$$N_t^i = \sum_{j=1}^{N_t} \mathbb{I}\{Class_j = Class_i\}, \quad \forall i \text{the} \qquad [13.9]$$

where $\mathbb{I}\{Class_j = Class_i\}$ denotes an indicator function that equals one if assets i and j belong to the same asset class and zero otherwise. To give an example, at the end of our sample period we have 52 assets: 20 commodities, 8 government bonds, 9 FX rates and 15 equity country indices. In this case, N_t^i is equal to 20 if asset i denotes a commodity, 8 if asset i denotes a bond and so on so forth.

Based on the above, our RB framework can be described by:

$$w_t^{RB,i} \cdot MCR_t^i = \frac{25\%}{N_t^i} \cdot \sigma_P, \quad \forall i \qquad [13.10]$$

where σ_P denotes the overall portfolio volatility and MCR is the marginal contribution to risk for each asset and is defined as the marginal change in portfolio volatility for a marginal change in the asset weight. To ease notation, we can drop the term $(25\% \cdot \sigma_P)$, as it is a common factor across all assets and our focus is really on the relative (and not absolute) distribution of risk. We can therefore re-write equation [13.10] using a proportionality symbol:

$$w_t^{RB,i} \cdot MCR_t^i \propto \frac{1}{N_t^i}, \quad \forall i \qquad [13.11]$$

We can contrast this against the standard RP allocation, where the weighted MCR is equal across all assets (instead of being inversely proportional to the number of assets in the same asset class):

$$w_t^{RP,i} \cdot MCR_t^i = constant, \quad \forall i \qquad [13.12]$$

12 To avoid any confusion in the terminology, when we use the term "risk-parity" we effectively refer to the equal risk contribution (ERC) scheme and not to the basic inverse-volatility scheme, which we call "volatility-parity".

The next step in defining the multiasset portfolio optimization for the carry portfolio is to introduce expected returns to the framework. In the history of portfolio optimization, starting from Markowitz's [MAR 52] modern portfolio theory, one of the most challenging parts has been the determination of expected returns. The absence of a well-agreed and accurate forecasting model[13], as well as the sensitivity/instability of mean-variance optimization to estimation errors[14] have been the primary reasons as to why risk-based investing (starting from minimum-variance portfolios) became progressively more popular with the passage of time.

Following the above, one could justifiably question why we should even bother introducing expected returns in our multiasset carry portfolio. But here lies probably one very simple, yet fundamental, idea. As already discussed in the introduction of the chapter and in equation [13.1], carry constitutes the expected returns of an asset if conditions remain the same. In other words, carry, which is readily available at any point in time and measured directly from the slope of the future/forward curve, is indeed a measure of expected returns that would even realize if the price of the asset does not move. We can therefore introduce the level of carry in our optimization framework and aim to optimize our allocation so to tilt the portfolio toward assets with higher carry potential at each point in time.

Following the above, we suggest extending the RB framework in order to increase the risk allocation (and therefore the gross weights) for assets that have higher level of carry, either positive or negative. To maintain transparency, we decide to take long positions for assets with positive carry and short positions for assets with negative carry as was the case in the time-series form of the strategy.

Regarding the absolute level of carry of each asset and given that our universe contains assets from different asset classes, it becomes likely that we would end up with a vector of expected returns that are not directly comparable to each other; given that we run an optimization across all assets, we must make sure that there is fair comparability in the expected return dimension. To achieve that we scale the level of carry for each asset with the level of volatility (measured over a rolling window of 100 days). Along these lines, we express the level of carry in risk units; hence, the ratio between carry and recent volatility expresses the *ex ante* Sharpe ratio of each asset at each rebalancing point:

$$Ex - ante\ Sharpe\ Ratio(i) = \frac{C_t^i}{\sigma_t^i},\quad \forall i \qquad [13.13]$$

13 Forecasting returns is probably the hardest empirical task in financial economics.

14 See [MER 80] and [CHO 93].

This measure of risk-adjusted carry constitutes a fairer metric to enter the optimization framework.

Putting all the pieces together:

– at the single asset level, assets with positive carry bear a long position and assets with negative carry bear a short position. In this way we succeed in *incorporating the time-series definition of carry in our optimized framework*;

– assets with higher level of risk-adjusted carry (either positive or negative) bear higher risk contribution (and therefore gross weight). Evidently, the relative strength of the carry signals does matter for the overall portfolio and therefore in this way we succeed in *incorporating the cross-sectional definition of carry in our optimized framework*;

– at the asset class level, we assume equal contribution to risk from each asset class, as long as all assets have the same *ex ante* Sharpe ratio. When this is not the case, the *risk allocation becomes proportional to the collective risk-adjusted carry of each asset class*, after taking into account all the *cross-correlation dependencies* between all assets from all asset classes.

Overall, by combining the proportionality statement [13.11] with equation [13.13], we end up with the final expression for the weighted marginal contribution to risk in our final long-short RB framework, which we plan to apply to construct the optimized (OPT) multiasset carry portfolio:

$$w_t^{OPT,i} \cdot MCR_t^i \propto \frac{|c_t^i|}{N_t^i \cdot \sigma_t^i}, \quad \forall i \qquad [13.14]$$

To ease notation, let us denote the right-hand side of the above relationship by s_t^i that stands for the "score" of each asset at each point in time that controls the overall risk contribution of this asset:

$$s_t^i \equiv \frac{|c_t^i|}{N_t^i \cdot \sigma_t^i}, \quad \forall i \qquad [13.15]$$

Solving for the optimized portfolio that satisfies [13.14] requires a proper risk-based optimization. This is achieved by restating our current problem in the following optimization format (see [BAL 15]):

$$w_t^{OPT} = \text{argmax} \sum_{i=1}^{N_t} |s_t^i| \cdot log(|w_t^i|)$$

$$\text{subject to } \sqrt{w_t' \cdot \Sigma_t \cdot w_t} \leq \sigma_{TGT}, \qquad [13.16]$$

where Σ_t denotes the covariance matrix of the universe and $\boldsymbol{w}_t$ denotes the vector of (net) weights. To put this in words, we solve for a long-short portfolio that maximizes the log-weighted carry, given a certain portfolio volatility target σ_{TGT}. It is easy to show that the Lagrangian of this optimization coincides with the proportionality expression [13.14], so the two expressions are indeed equivalent [BAL 15]. The optimization problem does not require any further constraints, but we must discuss a few final technical points:

– The weights of the optimization would not add up to 100% in gross terms due to the volatility constraint. One solution to this is to normalize the weights post-optimization, acknowledging of course that the portfolio volatility will obviously change. This is the approach that we follow in our results in the following pages, so that we always maintain an unlevered portfolio. When a volatility-targeted portfolio is required for the purposes of our analysis, we apply this after first normalizing the gross weights so that we can properly track the amount of required leverage.

– The optimization [13.16] preserves by construction – due to the use of the logarithmic function – the sign of the weights and no additional constraints are required. As a result, the signs of the initial weights are of critical importance as they will be preserved during the optimization procedure[15]. For this reason the initial vector of weights for the optimization [13.16] should contain positive values for assets with positive scores (assets in backwardation) and negative values for assets with negative scores (assets in contango). To make things easier for the optimization, we decide to start the search for the optimal allocation from the RB solution if all pairwise correlations were equal, which is the inverse-volatility score-adjusted solution (so if all pairwise correlations are indeed equal then we are already at the optimum):

$$w_t^{OPT,i,initial} = \frac{s_t^i / \sigma_t^i}{\sum_{j=1}^{N_t} |s_t^j| / \sigma_t^j}, \quad \forall i \qquad [13.17]$$

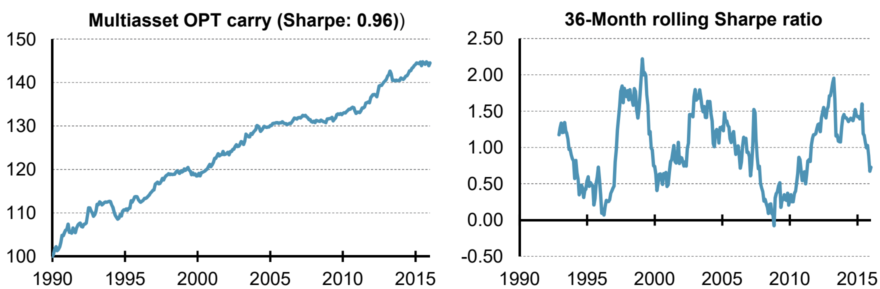
This concludes our long description of our suggestion for a multiasset carry portfolio that actively makes use of the relative strength of carry metrics, of the sign of the carry metrics as well as of the covariance structure of the universe.

As already discussed the OPT portfolio follows the TS portfolio in terms of which assets to go long and which assets to go short. However, the gross weights are

15 The objective function of the optimization [13.16] pushes the positive weights away from zero towards the positive territory, with the relative effects being more aggressive for assets with larger (positive) scores and equivalently pushes the negative weights away from zero toward the negative territory, with the effects being more aggressive for assets with larger (in absolute value, yet negative) scores.

purely determined by the optimization and, broadly speaking, we expect that assets with higher level of carry (over volatility) in absolute value should bear higher gross weights, so an XS type of ranking is also indirectly incorporated in the process. Finally, it becomes obvious that the OPT portfolio is not cash-neutral (as the XS portfolio is) but it will have proper directional tilts. However, contrary to the TS portfolio that is net long (short) if the majority of the assets are in backwardation (contango), the OPT portfolio might still end up being net long even if most assets are in contango, if the few assets that are in backwardation have much larger carry (over volatility) signals and also diversify much more risk away for the overall portfolio in a way that their gross allocation exceeds that of the assets in contango. This is generally the idea of residing to an optimization so as to optimally allocate risk across the various assets of all asset classes.

Given that our optimized framework should benefit mostly from an application across all assets from all asset classes, we only present of our results directly at the multiasset level[16]. Figure 13.7 presents the cumulative returns and the rolling Sharpe ratio of the unlevered multiasset OPT carry portfolio (so gross exposure is set at 100%), which is rebalanced on monthly basis using 100-day covariance matrix estimates between all 52 assets of our universe. Additionally, panel A of Table 13.9 reports performance statistics both for the unlevered strategy as well as for a levered version of the strategy that targets a volatility of 7%.



NOTE: The figure presents cumulative monthly returns for the optimized (OPT) multiasset carry portfolio as well as its 36-month rolling Sharpe ratio. The multiasset portfolio is constructed using a long-short risk-budgeting framework for 52 assets across FX, commodities, government bonds and equity indices. The portfolio is rebalanced monthly and the covariance structure is estimated using a 100-day window. The sample period is January 1990–January 2016.

Figure 13.7. *Multiasset optimized carry (unlevered)*

The multiasset OPT carry strategy, in its unlevered form, delivers positive average excess returns that are statistically strong (at 1% confidence) and a Sharpe ratio of 0.96. Similar to the TS carry strategy, it is positively skewed, but it also

16 Optimized portfolios for each asset class are available upon request.

comes along with higher kurtosis of 5.32; along these lines, it appears to exhibit superior positive tail behavior compared to the XS or TS variants of the strategy.

	Panel A: Optimized carry portfolio		Panel B: Alternative XS and TS combinations	
	Unlevered	Levered – 7% target	Equal weights – 7% target	Inv. volatility – 7% target
Average excess return (%)	1.42***	9.16***	7.58***	7.89***
Annualized volatility (%)	1.48	8.77	7.64	7.81
Skewness	0.26	0.30	–0.15	–0.13
Kurtosis	5.32	4.42	3.50	3.36
Maximum drawdown (%)	3.66	18.86	15.50	17.53
Sharpe ratio (annualized)	0.96	1.04	0.99	1.01
Sortino ratio (annualized)	1.76	1.96	1.70	1.76
Calmar ratio	0.39	0.49	0.49	0.45
Monthly turnover (%)	27.31	29.95	20.85	20.67
Average leverage	1×	7.1×	2.8×	3.0×
25th–75th percentiles	1×–1×	5.1×–9.1×	2.3×–3.2×	2.5×–3.5×

NOTE: Panel A presents performance statistics for the optimized (OPT) multiasset carry portfolio both on unlevered basis as well as on levered basis, assuming 7% target volatility. The multiasset portfolio is constructed using a long-short risk-budgeting framework for 52 assets across FX, commodities, government bonds and equity indices. For comparison purposes, panel B presents equally weighted and inverse-volatility weighted portfolios of multiasset cross-sectional (XS) and time-series (TS) portfolios, both levered at 7% target volatility. The portfolios are rebalanced monthly, the volatility target for the levered strategies is also applied on a monthly basis and all volatilities and covariance structure are estimated using a 100-day window. The statistical significance of the average return is indicated with *, ** and *** for 1, 5 and 10 confidence levels, using White [WHI 80] standard errors. The Sortino ratio is defined as the annualized excess return divided by downside volatility and the Calmar ratio is defined as the annualized geometric return divided by the maximum drawdown. In the estimation of the turnover, the absolute change in portfolio weights is normalized by the total gross exposure of the strategy in the beginning of the period. The sample period is January 1990–January 2016.

Table 13.9. *Performance statistics for multiasset carry strategies*

Most importantly, the fact that the OPT portfolio is optimized from a risk-diversification perspective, given the RB framework that is employed, results in a rather low portfolio volatility, equal to 1.48% (compared to 2.04% for XS and 2.60% for TS). Consequently, the OPT carry strategy requires more leverage (on average 7.1×) to achieve the required 7% level of volatility in its levered form.

Before presenting further results on the multiasset OPT portfolio, it is fair to compare it against simpler portfolios of the multiasset XS and TS portfolios that we presented in the previous sections. For this reason, panel B of Table 13.9 reports performance statistics for a static 50%–50% allocation between these portfolios as well as a dynamic inverse-volatility allocation between the same portfolios. Both combinations target a 7% level of volatility so that they can be compared with the levered OPT portfolio. We find that the OPT portfolio generates higher average returns and risk-adjusted returns than the simple portfolios of XS and TS strategies; the differences might not be very large, but we should appreciate that the OPT portfolio in fact consists of both XS and TS patterns so the similarities are more than expected. Probably the most important point in this comparison exercise relates to downside risk and skewness. The basic XS-TS portfolios exhibit negative skewness (–0.15 and –0.13), whereas the OPT portfolio exhibits positive and sizeable skewness (0.30). This leads to very pronounced differences in downside-risk-adjusted performance, as captured by the Sortino ratio: 1.96 for the OPT portfolio, as opposed to 1.70 and 1.76 for the two XS-TS portfolios.

Table 13.10 presents full-sample results from regressing the monthly returns of the OPT portfolio on the returns of multiasset XS and TS portfolios. All portfolios are in their levered form, targeting 7% volatility. As expected, the OPT portfolio is strongly exposed to both XS and TS portfolios either on a univariate basis or a multivariate basis[17]. However, in all cases the OPT portfolio manages to generate positive and statistically significant alpha, above and beyond what is already attained from the exposure to the underlying strategies. This constitutes evidence that the optimized framework adds value on top of the documented cross-sectional and time-series patterns.

Ann. alpha (%)	Cross-sectional (7%)	Time series (7%)	Adjusted R^2 (%)
5.08***	0.69***		33.3
2.73**		0.79***	50.4
2.33*	0.29***	0.63***	53.8

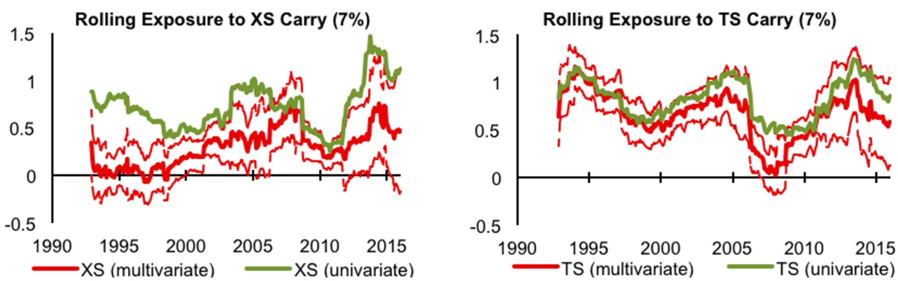
NOTE: The table presents the results of univariate and multivariate regressions of the optimized (OPT) multiasset carry portfolio on the respective cross-sectional (XS) and time-series (TS) carry portfolios. All strategies are levered at 7% target volatility. The portfolios are rebalanced monthly, the volatility target is also applied on a monthly basis and all volatilities and covariance structure for the OPT portfolio are estimated using a 100-day window. The regressions are conducted using monthly returns between January 1990 and January 2016. The statistical significance of the average return is indicated with *, ** and *** for 1, 5 and 10% confidence levels, using Newey and West [NEW 87] standard errors with six lags.

Table 13.10. *Exposures of the levered (7% vol.) multiasset optimized carry*

17 On a technical note, the fact that we use 100-day volatility estimates in the volatility-targeting overlay can give rise to serial correlation in the variables of the regressions. In order to control for this serial dependence, we use Newey and West [NEW 87] standard errors for the calculation of t-statistics, using six lags, as 100 business days are roughly 5–6 months.

As for the betas against XS and TS strategies, it is the one against the TS variant of carry that is stronger, both in magnitude and statistical significance. This is to a large extent to be expected, as the OPT strategy has been designed so that it is aligned with the TS strategy on the type of positions; additionally both the OPT and TS strategies exhibit directional tilts, whereas the XS strategy is net-zero. However, even if this is the case, the OPT strategy is also strongly exposed to the XS strategy even after controlling for its exposure to the TS strategy, as the multivariate regression results show in the last row of Table 13.10. The multivariate alpha is obviously smaller than the univariate alphas and its statistical significance falls, but still remains strong.

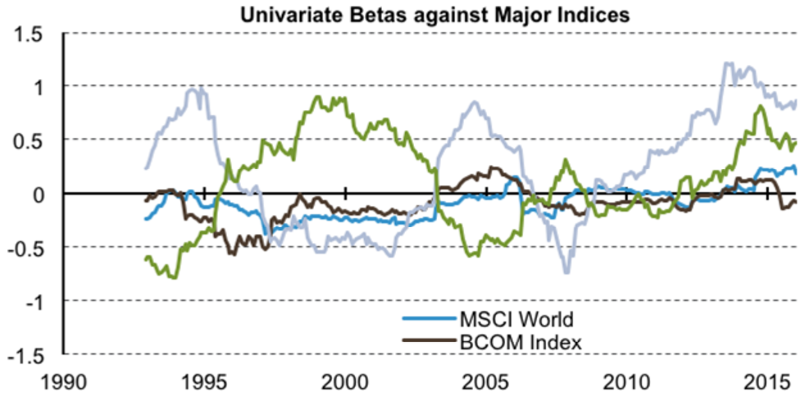
Corroborating these full-sample results, Figure 13.8 presents the 36-month rolling univariate betas and multivariate betas (including a 10% confidence interval band) of the OPT carry strategy on XS and TS multiasset carry strategies. It becomes obvious that controlling for TS, the beta to the XS strategy falls; however, it maintains its statistical significance for the most part of the post-2000 era. As for TS, the exposure of OPT to it remains almost unaffected by the inclusion of XS in the multivariate regression. The statistical significance is strong except for a few years in the late 2000s, when the exposure to XS picks up.



NOTE: The figure presents 36-month rolling betas of the optimized (OPT) multiasset carry portfolio on the respective cross-sectional (XS) and time series (TS) carry portfolios, using both univariate regressions as well as a multivariate regression; for the multivariate case the charts additionally include a 10% rolling confidence interval in dashed line based on Newey and West [NEW 87] standard errors with six lags. All strategies are levered at 7% target volatility. The portfolios are rebalanced monthly, the volatility target is also applied on a monthly basis and all volatilities and covariance structure for the OPT portfolio are estimated using a 100-day window. The regressions are conducted using monthly returns between January 1990 and January 2016.

Figure 13.8. *36-month rolling betas of the levered (7% vol.) multiasset optimized carry. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

As a last piece of performance diagnostics of the multiasset OPT carry strategy, Figure 13.9 presents the 36-month rolling univariate betas against the standard benchmark indices of the different asset class markets (MSCI World Index, Bloomberg Commodity Index, JPMorgan Aggregate Bond Index and Trade-weighted USD). Broadly speaking, the OPT carry strategy exhibits occasional directional tilts, which generally follow from its large dependence on the TS nature of signals. One important observation is that the strategy did not just benefit from the long-standing bond rally, as for about one third of time it exhibits a negative beta to the JPMorgan Aggregate Bond Index.



NOTE: The figure presents 36-month rolling univariate betas of the unlevered optimized (OPT) multiasset carry portfolio on four broad indices: MSCI World Index, Bloomberg Commodity (BCOM) Index, JPMorgan Aggregate Bond Index and Trade-Weighted USD. The regressions are conducted using monthly excess returns between January 1990 and January 2016.

Figure 13.9. *36-month rolling betas of the levered multiasset OPT carry. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

13.6. Is it crash risk?

So far, this chapter has documented strong multiasset carry dynamics that can be captured in various forms (XS, TS and OPT portfolios). The important question when it comes to a strategy with positive and statistically strong excess returns is whether the returns are positive because they compensate an investor for bearing some type of systematic risk (so that it is justified as "risk premium") or because they simply constitute an artifact of mispricing and behavioral biases.

As already explained earlier in the chapter, FX carry has been linked to FX crash risk as well as equity downside risk in the academic literature; hence, it is generally thought of as a cyclical short-volatility strategy. Without this being a formal test (yet), our FX carry strategies, both in XS and TS form, have been characterized by large negative skewness, which can possibly validate the academic claims.

Our task here is harder and broader. We have documented carry patterns across different asset classes and most importantly at the multiasset level, most of which have either lower negative skewness, if not positive. Can crash risk at the asset class level (or even broad equity crash risk) justify the positive returns?

We next present regression results between levered carry strategies across asset classes as well as at the multiasset level against a number of factors F:

$$r_{Carry,t} = const. + \boldsymbol{\beta}' \cdot \boldsymbol{F}_t + \epsilon_t \qquad [13.18]$$

When the factors are tradable portfolios, the constant of the regression can also be interpreted as "alpha". Our analysis is split between two sets of factors.

13.6.1. *Downside risk analysis*

First, we conduct a downside risk analysis, where carry portfolios of each asset class are regressed against asset-class-specific downside risk variables as well as against equity downside risk variables. The downside risk variables used for this analysis are:

– Market squared: The squared market return variable helps to uncover any dependence on large scale market moves, either positive or negative.

– Henrikson and Merton [HEN 81] downside risk variable:

$$r_{MKT,t,down} = -r_{MKT,t} \cdot \mathbb{I}\{r_{MKT,t} < 0\} \qquad [13.19]$$

The downside risk variable captures only the months with negative returns.

– Lettau *et al.* [LET 14] tail risk variable:

$$r_{MKT,t,tail} = -r_{MKT,t} \cdot \mathbb{I}\{r_{MKT,t} < -\sigma_{MKT}\} \qquad [13.20]$$

The tail risk variable captures only the months with negative returns that are more extreme than one standard deviation (σ_{MKT}). We use the full-sample standard deviation estimates, acknowledging the presence of forward-looking bias. The aim is to understand the negative tail dynamics and its effect on carry profitability, so this is not directly impacting our analysis.

We use the minus sign in equations [13.19] and [13.20] so that a negative exposure to all three downside variables can be interpreted as loading on some form of downside risk, whereas a positive exposure to these variables can be interpreted as a hedge against downside risk.

For the asset-class specific downside risk analysis, the "market" is proxied by the MSCI World Index for equities, the Bloomberg Commodity Index for commodities, the JPMorgan Aggregate Bond Index for government bonds and the Trade-Weighted USD index for FX[18]. For the equity downside risk analysis, the "market" is always the MSCI World Index.

Starting from the asset-class specific downside risk analysis (see Table 13.11, panels A1, B1, C1 and D), the evidence shows that FX carry, both in XS and TS, is heavily exposed to currency downside risk, which is generally in line with existing academic evidence. However, the only other sizeable exposure to downside risk appears for the XS (but not the TS) carry strategy is within commodities, which suffers when the underlying commodity market experiences large losses.

Contrary to the above, the equity TS carry strategy appears to offer a hedge against equity downside risk. Finally, as already documented at several points in this chapter, the government bond carry strategies (both XS and TS) are the only ones to load positively on their underlying market and therefore benefiting to a certain extent from the bond rally over the recent decades.

Regarding the equity downside risk analysis (see Table 13.11, panels A2, B2, C2 and D), apart from the equity TS carry strategy, which offers a hedge against equity downside risk, as already highlighted above, no other XS or TS carry strategy is exposed, either positively or negatively, to equity downside risk.

Interestingly, all betas of XS and TS carry strategies against the MSCI World Index are low in magnitude, even though they are statistically strong in most cases. In line with existing academic evidence, the FX carry strategy (XS and TS) exhibits a cyclical behavior as deduced by the positive and statistically significant equity market betas. Conversely, the bond carry strategy (XS and TS) is characterized by strong negative market betas, hence offering a hedge against equity market crashes.

The documented dynamics seem to imply that carry strategies across different asset classes constitute a diversified universe and therefore, when combined to a multiasset portfolio, most of the asset-class specific dynamics are expected to be suppressed. We investigate this after we first look at the equity volatility risk analysis.

18 The US 3-month Libor rate is used to construct excess monthly returns for these indices.

Cross-sectional carry strategies						Time-series carry strategies					
$\boldsymbol{Const.}$	$\boldsymbol{MKT}$	$\boldsymbol{MKT^2}$	$\boldsymbol{MKT_{down}}$	$\boldsymbol{MKT_{tail}}$	$\boldsymbol{Adj.R^2}$ (%)	$\boldsymbol{Const.}$	$\boldsymbol{MKT}$	$\boldsymbol{MKT^2}$	$\boldsymbol{MKT_{down}}$	$\boldsymbol{MKT_{tail}}$	$\boldsymbol{Adj.R^2}$ (%)
Panel A1: Commodities (market: BCOM Index)											
0.10	0.00				0.00	0.12	–0.22***				18.64
0.27**	–0.02	–0.95***			1.92	0.13	–0.22***	–0.04			18.10
0.41**	–0.11*		–0.20**		1.01	0.18	–0.24***		–0.04		18.16
0.26**	–0.07			–0.16**	1.16	0.16	–0.24***			–0.04	18.21
Panel A2: Commodities (market: MSCI World Index)											
0.07	0.06**				1.25	0.11	–0.10***				4.24
0.11	0.05*	–0.21			0.71	0.08	–0.10***	0.19			3.70
0.05	0.06		0.01		0.61	0.11	–0.10*		0.00		3.62
0.12	0.03			–0.05	0.79	0.11	–0.10**			0.00	3.62
Panel B1: Govt. bonds (market: JPM Aggregate Bond Index)											
0.46***	0.38***				9.57	0.48***	0.57***				15.34
0.53***	0.40***	–2.76			9.33	0.52***	0.59***	–1.55			14.87
0.66***	0.24*		–0.32		9.60	0.63***	0.48***		–0.22		15.00
0.55***	0.31***			–0.24	9.57	0.51***	0.55***			–0.07	14.83
Panel B2: Govt. bonds (market: MSCI World Index)											
0.58***	–0.09***				3.69	0.68***	–0.12***				4.51
0.60***	–0.09***	–0.14			3.12	0.74***	–0.13***	–0.30			4.05
0.60***	–0.09*		–0.01		3.07	0.71***	–0.13**		–0.02		3.91
0.58***	–0.09**			0.00	3.07	0.64***	–0.10**			0.04	3.98

Panel C1: FX (market: Trade-Weighted USD)											
0.16	–0.09				0.55	0.31**	–0.15				1.37
0.50***	–0.11	–11.87***			6.95	0.55***	–0.16**	–8.37**			4.01
0.75***	–0.58***		–0.89***		4.90	0.84***	–0.59***		–0.81***		4.57
0.34***	–0.30**			–0.47**	2.85	0.47***	–0.34***			–0.42**	2.95
Panel C2: FX (market: MSCI World Index)											
0.16	0.12***				6.30	0.32***	0.12***				5.49
0.28**	0.11***	–0.63			6.65	0.26**	0.12***	0.35			5.14
0.31	0.07		–0.09		6.04	0.22	0.15**		0.06		5.02
0.17	0.12***			–0.01	5.70	0.21	0.17***			0.11	5.78
Panel D: Equity Indices (market: MSCI World Index)											
0.18*	–0.05**				1.45	0.21*	–0.18***				12.07
0.22*	–0.05**	–0.17			0.91	–0.01	–0.16***	1.14**			14.04
0.15	–0.04		0.02		0.84	–0.26*	–0.03		0.28***		14.23
0.11	–0.02			0.06	1.25	–0.06	–0.07			0.25***	15.64

NOTE: The table presents the results from regressing XS and TS carry portfolios of each asset class to the respective market (BCOM Index for commodities, JPMorgan Aggregate Bond Index for government bonds, Trade-Weighted USD for FX and MSCI World Index for equity indices) as well as a number of associated downside risk variables. All strategies are levered at 7% target volatility. Any statistical significance is indicated with *, ** and *** for 1, 5 and 10% confidence levels, using Newey and West [NEW 87] standard errors with six lags. The constant of each regression is multiplied by 100. The regressions are conducted using monthly returns between January 1990 and January 2016.

Table 13.11. *Downside risk analysis for XS and TS portfolios of each asset class*

13.6.2. *Equity volatility risk analysis*

Next, we conduct an equity volatility risk analysis, where carry portfolios of each asset class are regressed against monthly changes in VIX (see Table 13.12). Broadly in line with the findings so far, the FX carry (both XS and TS) is very strongly exposed to changes of VIX, hence justifying the academic evidence in this space. Additionally, the XS form of FX carry, which is the most heavily studied form of carry, maintains a strong and positive market beta alongside a negative exposure on the changes in VIX. The only other specification with negative exposure on the changes in VIX is the commodity XS carry strategy, which however turns insignificant when we control for the overall equity market.

Contrary to the above, government bonds appear to provide a hedge against changes in VIX, in line with our earlier findings. It is worth commenting that all TS carry strategies, except for FX, seem to constitute a hedge against increases in equity market volatility.

Cross-sectional carry strategies				Time-series carry strategies			
$Const.$	$MSCI$	ΔVIX	$Adj.R^2$ (%	$Const.$	$MSCI$	ΔVIX	$Adj.R^2$ (%)
Commodities							
0.08		–0.06**	1.37	0.10		0.08**	2.35
0.08	0.03	–0.04	0.91	0.12	–0.10***	0.01	3.86
Government bonds							
0.57***		0.07**	2.12	0.64***		0.07**	1.72
0.58***	–0.08**	0.01	3.22	0.66***	–0.12***	0.00	3.60
FX							
0.18		–0.12***	6.11	0.34***		–0.10***	4.17
0.16	0.08**	–0.07*	7.01	0.32***	0.09**	–0.04	5.43
Equity indices							
0.17*		0.01	0.03	0.16		0.09***	2.81
0.19*	–0.08***	–0.05	1.53	0.20*	–0.22***	–0.06	11.74

NOTE: The table presents the results from regressing XS and TS carry portfolios of each asset class to the MSCI World Index and to monthly changes in VIX (ΔVIX). All strategies are levered at 7% target volatility. Any statistical significance is indicated with *, ** and *** for 1, 5 and 10% confidence levels, using Newey and West [NEW 87] standard errors with six lags. The constant of each regression and the exposure to ΔVIX are multiplied by 100. The regressions are conducted using monthly returns between January 1990 and January 2016.

Table 13.12. *Volatility risk across XS and TS carry portfolios for each asset class*

All in all, asset-class-specific or equity downside risks do not seem to justify the positive returns of carry strategies with the only exception being within FX. In other words, crash risk does not appear to provide a unifying framework for explaining the carry patterns. We finally look at the multiasset level.

13.6.3. *Multiasset carry analysis*

Having econometrically established the dependencies of carry strategies of each asset class with the respective market as well as with the overall global equity market, we conclude the empirical analysis of this chapter with regression results for the multiasset XS, TS and OPT carry portfolios in Table 13.13.

$Const.$	$MSCI$	$MSCI^2$	$MSCI_{down}$	$MSCI_{tail}$	ΔVIX	$Adj. R^2$(%)
XS Multiasset						
0.49***	0.02					0.23
0.63***	0.01	–0.76				0.94
0.59**	–0.01		–0.06			–0.26
0.50***	0.02			–0.01		–0.39
0.49***					–0.06	1.46
0.50***	–0.03				–0.08**	1.01
TS Multiasset						
0.70***	–0.13***					6.13
0.57***	–0.11***	0.68*				6.45
0.43**	–0.04		0.16*			6.46
0.49***	–0.04			0.20***		8.22
0.66***					0.05	1.03
0.69***	–0.16***				–0.05	5.78
OPT Multiasset						
0.78***	–0.08**					1.80
0.81***	–0.08**	–0.15				1.20
0.80***	–0.09		–0.01			1.17
0.74***	–0.06			0.04		1.25
0.77***					0.03	0.33
0.79***	–0.10**				–0.03	1.39

NOTE: The table presents the results from regressing multiasset XS, TS and OPT carry portfolios to the MSCI World Index and a number of associated downside risk variables as well as changes in VIX. All strategies are levered at 7% target volatility. The constant of each regression and the exposure to ΔVIX are multiplied by 100. The regressions use monthly returns between January 1990 and January 2016.

Table 13.13. *Downside and volatility risk for multiasset carry strategies*

The multiasset XS carry portfolio is effectively equity market neutral and only exhibits a negative exposure in changes in VIX, which might justify the premium as compensation for volatility risk (in line with [KOI 17]). Instead, the multiasset TS carry portfolio exhibits negative equity market betas, which generally remain significant unless we control for equity downside risk, in which case the portfolio appears to constitute a hedge against this risk. So, if anything, the TS carry appears to be a good diversifier for an equities portfolio.

Given the above dependences, the multiasset OPT carry portfolio appears to benefit from the optimized risk allocation and completely eliminates any exposure to downside or volatility risk. It only exhibits a small in magnitude – at times significant – beta against the market. This finding is extremely interesting and highlights the benefits of forming multiasset portfolios, as well as employing an optimization framework to optimize the risk allocation.

13.7. Concluding remarks

The carry trade is probably the most well-known trading strategy in the foreign exchange market, but there is little evidence and analysis on a multiasset scale. This chapter contributes to the literature by first extending the concept of carry across asset classes and second by highlighting the benefits of diversification that an investor can enjoy when invested in a systematic multiasset carry strategy.

Carry signals are found to have predictive power for future asset returns, not just within FX, but also across commodities, equity indices and government bonds, hence offering an additional source of return for an investor who looks for yield, especially during sideways markets. Most importantly, carry strategies outside FX do not appear to have significant exposure to downside risk – either with respect to their respective market or to the broad equity market – hence justifying their inclusion to a multiasset allocation framework.

The greatest benefit from extending carry to a multiasset concept is, in fact, the diversification potential from combining carry strategies from different asset classes. The fact that not all carry strategies fail at the same time renders the multiasset carry portfolio robust to equity downside risk and volatility spikes. We have provided an novel risk-based optimization framework that optimizes the allocation of risk across asset classes, while tilting the portfolio toward asset classes that bear higher collective carry at any point in time. In this way, we have managed to optimally combine the relative strength (cross-sectional) with the absolute (time series) nature of carry signals while also accounting for the multiasset covariance structure. Based on this analysis, the optimized multiasset carry portfolio has an attractive risk-return profile, with positive skewness and a small and negative exposure to the broad equity market, without being exposed to any downside risk.

13.8. Appendix: Estimating the carry metric for each asset class

In order to estimate the level of carry of each asset from each asset class at the end of each month, we can theoretically estimate the slope of the futures curve, as already explained in the main body of the chapter. However, various idiosyncrasies of the different asset classes that we focus on make the estimation of carry a tedious process that makes use of various data sources and required careful preprocessing and data cleaning. We explain our approach separately for each asset class; Table 13.14 summarizes the various carry metrics.

Asset class	Chosen metric	Alternatives
FX	$\frac{Spot_t - Fwd_t^{1M}}{Fwd_t^{1M}}$	$r_t^* - r_t$ $\frac{1}{T_2 - T_1} \cdot \frac{Fut_t^{T_1} - Fut_t^{T_2}}{Fut_t^{T_2}}$
Equity indices	$\frac{1}{T_2 - T_1} \cdot \frac{Fut_t^{T_1} - Fut_t^{T_2}}{Fut_t^{T_2}}$ Seasonally adjusted (12 months)	$\frac{Spot_t - Fut_t^{1M,intrpl}}{Fut_t^{1M,intrpl}}$ Seasonally adjusted (12 months)
Commodities	$\frac{1}{T_2 - T_1} \cdot \frac{Fut_t^{T_1} - Fut_t^{T_2}}{Fut_t^{T_2}}$ Seasonally adjusted (12 months)	$\frac{Fut_t^{T_1} - Fut_t^{T_1+1y}}{Fut_t^{T_1+1y}}$
Government bonds	$\frac{Spot_t^{9Y11M,intrpl} - Fut_t^{1M;10Y,Synth}}{Fut_t^{1M;10Y,Synth}}$	$\frac{1}{T_2 - T_1} \cdot \frac{Fut_t^{T_1} - Fut_t^{T_2}}{Fut_t^{T_2}}$

Table 13.14. *How to measure carry across asset classes*

– FX: Accessing the foreign exchange market is typically achieved either directly in the spot market or alternatively via forward contracts. For this reason, our chosen metric for the slope of the futures/forward curve makes use of spot prices and 1-month forward prices, all collected from Bloomberg. As alternatives, we could theoretically use (i) the 3-month Libor rate differential between the foreign and the USD markets or (ii) the front and first back futures contracts (maturing after T_1 and T_2 days), adjusting the slope by the difference in days-to-maturity ($T_2 - T_1$), so that we can allow for cross-sectional ranking between currencies. The first alternative (rate differential) results in carry metrics that are very largely correlated with our preferred metric; the correlations range from 88.1% for NZD up to 99.2% for JPY. This is largely expected due to the covered interest rate parity. The second alternative is not tested as there are no good quality historical data for the back futures contracts for most currencies; the liquidity of these back contracts is almost non-existent and only picks up a few days before maturity, when roll-overs from the front contract start taking place.

– Equity indices: We have two options. Our preferred metric is the slope of the futures curve, as estimated by the front and first back futures contracts, adjusted by the difference in days-to-maturity $(T_2 - T_1)$. Additionally, we apply a seasonality adjustment, which is trivially a 12-month moving average filter of the raw carry metric, following the documentation of strong seasonal patterns within equity indices and commodities, but not within FX or government bond markets (see [KEL 16, BAL 16]). Baz *et al.* [BAZ 15] and Koijen *et al.* [KOI 17], who also look at multiasset carry strategies, similarly seasonally adjust the carry metrics for equity indices and commodities. An alternative for equity indices would be to use the front and the first back futures contracts in order to estimate (using interpolation) the futures price for a maturity of 1 month and compare this with the prevailing spot price of the index; seasonal adjustment should also apply. One important observation (and warning) here is that these two carry metrics would have different values and even different signs, if the futures curve happens to be humped in the short end.

– Commodities: Given that commodities are generally accessed via futures contracts, we have one option, and that is to estimate the slope of the curve using the front and first back futures contracts, adjusted by the difference in days-to-maturity $(T_2 - T_1)$. As for equity indices, a 12-month moving average filter is applied in order to eliminate any seasonal patterns. An alternative definition would estimate the slope using the front futures contract and the contract expiring 1 year after (these contracts are relatively liquid in the commodity markets). This estimate is by construction free from any seasonal patterns and therefore no further adjustment is required.

– Government bonds: The quality of historical futures data, except for the front contract, is very poor for government bonds. This does not really allow us to estimate the slope of the curve using the front and first back futures contracts, adjusted by the difference in days-to-maturity $(T_2 - T_1)$, except for a subset of our universe and for a subset of our sample period. Instead, we follow Koijen *et al.* [KOI 17] and estimate the slope of the curve using the spot price of a bond with maturity of 9 years and 11 months and a synthetic 10-year bond futures price with maturity of 1 month. To achieve this, we make use of zero-coupon yield data from Bloomberg for maturities of 9 and 10 years. The 9 years and 11 months yield is therefore trivially estimated using linear interpolation:

$$y_t^{9Y11M,intrpl} = \frac{1}{12} \cdot y_t^{9Y} + \frac{11}{12} \cdot y_t^{10Y} \qquad [13.21]$$

The spot bond price with maturity of 9 years and 11 months is therefore:

$$Spot_t^{9Y11M,intrpl} = \frac{1}{\left(1+y_t^{9Y11M,intrpl}\right)^{9+\frac{11}{12}}} \quad [13.22]$$

Finally, the futures price of a 10-year bond with maturity of 1 month is trivially equal to the respective bond price accrued to the risk-free rate (r_t) for a month:

$$Fut_t^{1M;10Y,Synth} = \frac{1+r_t}{\left(1+y_t^{10Y}\right)^{10}} \quad [13.23]$$

For the risk-free rate, we use the 3-month Libor rate for the respective country. Estimating the slope of the futures curve should then be straightforward.

13.9. Bibliography

[ACK 16] ACKERMANN F., POHL W., SCHMEDDERS K., *Optimal and Naive Diversification in Currency Markets*, available at SSRN 2184336, 2016.

[AHM 13] AHMERKAMP J.D., GRANT J., *The Returns to Carry and Momentum Strategies*, available at SSRN 2227387, 2013.

[ANG 07] ANG A., BEKAERT G., "Stock return predictability: is it there?", *Review of Financial Studies*, vol. 20, no. 3, pp. 651–707, 2007.

[ASN 13] ASNESS C.S., MOSKOWITZ T.J., PEDERSEN L.H., "Value and momentum everywhere", *Journal of Finance*, vol. 68, no. 3, pp. 929–985, 2013.

[BAL 15] BALTAS N., "Trend-following, risk-parity and the influence of correlations", in JURCZENKO E. (ed.), *Risk-Based and Factor Investing*, ISTE Press, London and Elsevier, Oxford, 2015.

[BAL 16] BALTAS N., "Multi-asset seasonality and trend-following strategies", *Bankers, Markets & Investors,* vol. 140, pp. 47–62, 2016.

[BAL 14] BALTAS N., JESSOP D., JONES C., Harvesting cross-asset value, UBS Investment Research, 2014.

[BAL 13] BALTAS N., JESSOP D., JONES C. *et al*., Trend-following meets risk-parity, UBS Investment Research, 2013.

[BAL 14] BALTAS N., JESSOP D., JONES C., ZHANG H. *et al*., Correlation, de-correlation and risk-parity, UBS Investment Research, 2014.

[BAR 15] BARROSO P., SANTA-CLARA P., "Beyond the carry trade: optimal currency portfolios", *Journal of Financial and Quantitative Analysis*, vol. 50, no. 5, pp. 1037–1056, 2015.

[BAZ 15] BAZ J., GRANGER N.M., HARVEY C.R. *et al.*, *Dissecting Investment Strategies in the Cross Section and Time Series*, available at SSRN 2695101 2015.

[BEK 16] BEKAERT G., PANAYOTOV G., *Good Carry, Bad Carry*, available at SSRN 2600366, 2016.

[BHA 07] BHANSALI, V., "Volatility and the carry trade", *Journal of Fixed Income,* vol. 17, no. 3, pp. 72–84, 2007.

[BHA 15] BHARDWAJ G., GORTON G.B., ROUWENHORST K.G., *Facts And Fantasies About Commodity Futures Ten Years Later*, available at SSRN 2610772, 2015.

[BRU 12] BRUDER B., RONCALLI T., *Managing Risk Exposures Using the Risk Budgeting Approach*, available at SSRN 2009778, 2012.

[BRU 08] BRUNNERMEIER M.K., NAGEL S., PEDERSEN L.H., "Carry Trades and Currency Crashes", *NBER Macroeconomics Annual*, vol. 23, no. 1, pp. 313–348, 2008.

[BRU 09] BRUNNERMEIER M.K., PEDERSEN L.H., "Market Liquidity and Funding Liquidity" *Review of Financial Studies*, vol. 22, no. 6, 2201–2238, 2009.

[BUR 11] BURNSIDE C., EICHENBAUM M., KLESHCHELSKI, I., REBELO S., "Do Peso Problems Explain the Returns to the Carry Trade?", *Review of Financial Studies*, vol. 24, no. 3, pp. 853–891, 2011.

[BUR 11] BURNSIDE C., EICHENBAUM M., REBELO S., "Carry Trade and Momentum in Currency Markets", *Annual Review of Financial Economics*, vol. 3, no.1, pp. 511–535, 2011.

[CAM 88] CAMPBELL J.Y., SHILLER R.J., "The dividend-price ratio and expectations of future dividends and discount factors", *Review of Financial Studies*, vol. 1, no. 3, pp. 195–228, 1988.

[CAM 91] CAMPBELL J.Y., SHILLER, R.J., "Yield spreads and interest rate movements: A bird's eye view", *Review of Economic Studies*, vol. 58, no. 3, 495–514, 1991.

[CHO 93] CHOPRA V.K., ZIEMBA W.T., "The Effect of Errors in Means, Variances, and Covariances on Optimal Portfolio Choice", *Journal of Portfolio Management*, vol. 19, no. 2, pp. 6–11, 1993.

[DAN 17] DANIEL K.D., HODRICK R.J., LU Z., "The carry trade: risks and drawdowns", *Critical Finance Review*, forthcoming 2017.

[DOB 14] DOBRYNSKAYA V., "Downside market risk of carry trades", *Review of Finance*, vol. 18, no. 5, pp. 1885–1913, 2014.

[DOS 15] DOSKOV N., SWINKELS L., "Empirical evidence on the currency carry trade", 1900–2012, *Journal of International Money and Finance*, vol. 51, pp. 370–389, 2015.

[ENG 96] ENGEL, C., "The forward discount anomaly and the risk premium: a survey of recent evidence", *Journal of Empirical Finance*, vol. 3, no. 2, pp. 123–192, 1996.

[ERB 06] ERB C.B., HARVEY C.R., “The strategic and tactical value of commodity futures”, *Financial Analysts Journal*, vol. 62, no. 2, pp. 69–97, 2006.

[ERB 16] ERB C.B., HARVEY C.R., “Conquering misperceptions about commodity futures investing”, *Financial Analysts Journal*, vol. 72, no. 4, pp. 26–35, 2016.

[FAM 84] FAMA E.F., “Forward and spot exchange rates”, *Journal of Monetary Economics*, vol. 14, no. 3, pp. 319–338, 1984.

[FAM 87] FAMA E.F., BLISS R.R., “The information in long-maturity forward rates”, *American Economic Review*, vol. 77, no. 4, pp. 680–692, 1987.

[FAM 88] FAMA E.F., FRENCH K.R., “Dividend yields and expected stock returns”, *Journal of Financial Economics*, vol. 22, no. 1, pp. 3–25, 1988.

[FAMA 93] FAMA E.F., FRENCH K.R., “Common risk factors in the returns on stocks and bonds”, *Journal of Financial Economics*, vol. 33, no. 1, pp. 3–56, 1993.

[FAR 15] FARHI E., FRAIBERGER S.P., GABAIX X. *et al*., *Crash Risk in Currency Markets*, available at SSRN: 1397668, 2015.

[FAR 16] FARHI E., GABAIX X., “Rare disasters and exchange rates”, *The Quarterly Journal of Economics*, vol. 131, no. 1, pp. 1–52, 2016.

[FIT 16] FITZGIBBONS S., FRIEDMAN J., POMORSKI L. *et al*., *Long-Only Style Investing: Don’t Just Mix, Integrate*, available at SSRN 2802849, 2016.

[GOR 13] GORTON G., HAYASHI F., ROUWENHORST K.G., “The fundamentals of commodity futures returns”, *Review of Finance*, vol. 17, no. 1, pp. 35–105, 2013.

[GOR 06] GORTON G., ROUWENHORST K.G., “Facts and fantasies about commodity futures”, *Financial Analysts Journal*, vol. 62, no. 2, pp. 47–68, 2006.

[GOY 15] GOYAL A., JEGADEESH N., *Cross-Sectional and Time-Series Tests of Return Predictability: What is the Difference*?, available at SSRN: 2610288, 2015.

[HAN 80] HANSEN L.P., HODRICK R.J., “Forward exchange rates as optimal predictors of future spot rates: an econometric analysis”, *Journal of Political Economy*, vol. 88, no. 5, pp. 829–853, 1980.

[HEN 91] HENRIKSSON R.D., MERTON R.C., “On market timing and investment performance II, statistical procedures for evaluating forecasting skills”, *Journal of Business*, vol. 54, no. 4, pp. 513–533, 1991.

[ILM 11] ILMANEN A., *Expected Returns: an Investor’s Guide to Harvesting Market Rewards*, John Wiley & Sons, 2011.

[JEG 93] JEGADEESH N., TITMAN S., “Returns to buying winners and selling losers: implications for stock market efficiency”, *Journal of Finance*, vol. 48, no. 1, pp. 65–91, 1993.

[JEG 01] JEGADEESH N., TITMAN S., "Profitability of momentum strategies: an evaluation of alternative explanations", *Journal of Finance*, vol. 56, no. 2, pp. 699–720, 2001.

[JES 13] JESSOP D., JONES C., LANCETTI S. *et al.*, "Understanding risk parity", *UBS Investment Research*, 2013.

[JUR 14] JUREK J.W., "Crash-neutral currency carry trades", *Journal of Financial Economics*, vol. 113, no. 3, pp. 325–347, 2014.

[KEL 16] KELOHARJU M., LINNAINMAA J.T., NYBERG P., "Return seasonalities", *Journal of Finance*, vol. 71, no. 4, pp. 1557–1590, 2016.

[KEY 30] KEYNES J.M., *A Treatise on Money*, Harcourt Brace and Company, 1930.

[KOI 17] KOIJEN R.S., MOSKOWITZ T.J., PEDERSEN L.H. *et al.*, "Carry", *Journal of Financial Economics*, forthcoming 2017.

[LET 14] LETTAU M., MAGGIORI M., WEBER M., "Conditional risk premia in currency markets and other asset classes", *Journal of Financial Economics*, vol. 114, no. 2, pp. 197–225, 2014.

[LUS 11] LUSTIG H., ROUSSANOV N., VERDELHAN A., "Common risk factors in currency markets", *Review of Financial Studies*, vol. 24, no. 11, pp. 3731–3777, 2011.

[LUS 14] LUSTIG H., ROUSSANOV N., VERDELHAN A., "Countercyclical currency risk premia", *Journal of Financial Economics*, vol. 111, no. 3, pp. 527–553, 2014.

[LUS 07] LUSTIG H., VERDELHAN A., "The cross section of foreign currency risk premia and consumption growth risk", *American Economic Review*, vol. 97, no. 1, pp. 89–117, 2007.

[MAR 52] MARKOWITZ H., "Portfolio selection", *Journal of Finance*, vol. 7, no. 1, pp. 77–91, 1952.

[MEN 12] MENKHOFF L., SARNO L., SCHMELING M. *et al.*, "Carry trades and global foreign exchange volatility", *Journal of Finance*, vol. 67, no. 2, pp. 681–718, 2012.

[MER 80] MERTON R.C., "On estimating the expected return on the market: an exploratory investigation", *Journal of Financial Economics*, vol. 8, no. 4, pp. 323–361, 1980.

[MOS 12] MOSKOWITZ T J., OOI Y H., PEDERSEN L H., "Time Series Momentum", *Journal of Financial Economics*, vol. 104, no. 2, pp. 228–250, 2012.

[NEW 87] NEWEY W.K., WEST K.D., "A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix", *Econometrica,* vol. 55, no. 3, pp. 703–708, 1987.

[OLS 14] OLSZWESKI F., ZHOU G., "Strategy diversification: combining momentum and carry strategies within a foreign exchange portfolio", *Journal of Derivatives & Hedge Funds*, vol. 19, no. 4, pp. 311-320, 2014

[RAF 12] RAFFERTY B., "Currency returns, skewness and crash risk", *Skewness and Crash Risk*, available at SSRN: 2022920, 2012.

[SIL 00] SILL K., "Understanding asset values: stock prices, exchange rates, and the peso problem", *Business Review*, 2000.

[WHI 80] WHITE H., "A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity", *Econometrica*, vol.48, no. 4, pp. 817–838, 1980.

[YAN 13] YANG F., "Investment shocks and the commodity basis spread", *Journal of Financial Economics*, vol. 110, no. 1, pp. 164–184, 2013.

14

Diversification and the Volatility Risk Premium

The volatility risk premium (VRP) found in options has paid off persistently across different assets, different asset classes and over time. A consistent short volatility position using options or volatility swaps has produced attractive risk-adjusted returns because of exposure to VRP. In this chapter, we have extended the study of the VRP to include not only equity indices but also commodities, government bonds and currencies. Using volatility swap returns as a measure of the payoff to the VRP, we see that the returns to a short volatility position are correlated to the volatility of the underlying instrument and to other VRPs in the same asset class. We also find that the returns are relatively uncorrelated to the VRPs of other asset classes and to the traditional equity factors represented by pure factor portfolios (PFPs). Finally, we show that the multiasset class VRP portfolio studied in this chapter has very competitive risk-adjusted returns.

14.1. Introduction

Volatility is defined as a measure of the variation in the price of an asset over time. Higher volatility is naturally associated with greater potential for larger losses. The desire to manage the volatility or the distribution of asset returns has been met by financial markets with investment products that can price this risk using forward looking measures of volatility – commonly referred to as implied volatility. In a world characterized by perfectly efficient and frictionless markets, we would expect actual volatility to, on average, equal implied volatility. In other words, the price of hedging should be an actuarially unbiased estimate of the future volatility of an asset.

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As participants in options and related derivative securities have found however, the price of hedging tends to be systematically "too high" for certain types of assets. This premium, commonly referred to as the VRP, has been documented across a variety of asset classes. For example, Bakshi and Kadapia [BAK 03] document a positive risk premium in S&P500 Index options. Trolle and Schwatz [TRO 10] document the premium in crude oil and gas, and find that the premium is much larger for crude oil[1].

The VRP is a relatively "new" risk premium that, until recently, was neither specifically referenced in the financial literature nor explicitly measured in investment tools. Notably asset allocation strategies of institutional investors seldom include an allocation to this premium as a source of returns in the same manner as, for example, the equity risk premium or the default risk premium. In part, the manner in which financial literature dealt with the VRP may have been due to the lack of traded financial instruments that allowed direct access to volatility. Instead, volatility was viewed as a property of almost all investments and if investors wanted less volatility they would adjust the composition of their portfolio by holding fewer risky assets or more of the risk-free security.

The notion of implied volatility is central to the definition of the VRP. The seminal paper by Black and Scholes [BLA 73] resulted in a framework to value options and a method to estimate an option's exposure to the underlying asset, interest rates, time and volatility. Using this framework, it was easy to see that option prices were primarily influenced by expectations of future volatility. Option market prices and the Black–Scholes (BS) model could be used to recover the volatility implied in the prevailing market prices of options. This derived implied volatility measure was the first instance where investors were able to translate option prices into an explicit forecast of future volatility.

Initially one could gain access to volatility using listed equity and equity index options by hedging away additional risks present in options that are not associated with volatility. More recently, the desire to express a view on volatility has resulted in a number of trading vehicles that allowed investors to gain direct access to volatility. These include volatility and variance swaps in the OTC market and the volatility index (VIX) complex introduced by the Chicago Board Options Exchange (CBOE) in the listed market. Volatility and variance swaps are priced using prevailing implied measures. The return is derived from the respective difference

1 In the growing literature on this topic, it is sometimes defined as the difference between actual and implied volatility, as opposed to the difference between implied and actual. This obviously results in those papers finding a negative VRP as opposed to the positive VRP documented in this chapter. We follow the convention of examining the difference between implied and actual as a positive value as it coincides with the notion that implied volatility is an upward biased estimator of future volatility.

between the subsequent realized volatility as measured by the standard deviation or variance of daily underlying returns and the initial implied volatility or variance. This contract payoff (the difference between realized minus implied) has become the standard definition of the VRP, although the method used to estimate the implied volatility is independent of any model.

The goal of this chapter is to examine the investment merits of the VRP. We first assess the degree to which the VRP is present as a potential source of return in a variety of different asset classes including equities, fixed income, currencies and commodities. We study the relationship between the magnitude of the VRP and the volatility of the underlying asset. Finally, we examine the premia in a portfolio context, with the goal of assessing the performance of diversified VRP portfolios. The performance of these portfolios is then evaluated in terms of pure factors portfolios to determine the extent to which they are related to more common return divers. Our main findings are that (i) VRPs exhibit low correlation across asset classes and higher correlation within asset classes suggesting that investors should consider a diversified portfolio of VRPs across asset classes as a source of return in their portfolio, and (ii) that VRP returns are separate and distinct from those captured by PFPs suggesting that they would enhance a typical investment portfolio by providing additional diversification at the portfolio level.

14.2. Definition of VRP

The VRP is formally defined as the difference between the risk neutral volatility and the expected total return volatility of an asset. It is usually thought of as the difference between the option implied volatility, representing the risk neutral estimate, and the expected realized volatility. Because the expected realized volatility is generally unobservable, practitioners typically calculate it as the difference between some implied volatility measure for an underlying asset and the realized volatility for the same underlying asset over some specified period – usually the time to expiration for the derivative contract in question. While this seems like a straight forward description, there are some subtleties involved.

One subtlety has to do with implied volatility. The term “implied volatility” originally came from the process of discovering the volatility input into the BS options pricing model that explained the observed option prices. The idea was that this volatility estimate could be interpreted as the market’s estimate of the underlying future volatility over the life of the option or the volatility forecast “implied” by the options market. Assumptions underlying the BS model include constant volatility, underlying assets follow a geometric Brownian motion process, lognormally distributed and statistically independent asset returns, the ability of market participants to borrow and lend at the risk free rate and zero transaction costs. Empirical research and common sense clearly show that these assumptions are not entirely accurate. Volatility is not constant and asset returns are not lognormally distributed. The underlying asset prices exhibit serial correlation and the borrow/lend rates are not equal and depend upon a number of factors. And of course, transaction costs can be significant.

Another subtlety involves calculating implied volatility for all options on a particular underlying by inverting the BS pricing model resulting in different implied volatilities for each option. Even worse, the calculated implied volatilities show a clear pattern in that there is a direct relationship between implied volatilities and the distance that the strike price of the option is above or below the current underlying price. Implied volatilities for equity and equity index option strikes below the current underlying spot price generally had higher implied measures than options with strikes higher than the current spot price. This phenomenon is commonly referred to as the option skew and it is present in almost all asset classes and markets (see [BAT 96]). The presence of multiple measures of implied volatilities lead to a challenge in measuring the VRP, and it became commonplace to use an average of the different values or a simpler measure based on the at-the-money option.

An improvement in the measurement of the VRP was the contribution by Demeterfi, Derman, Kamal and Zou (DDKZ) [DEM 99] who found a way around these problems by showing that a properly weighted average of all out-of-the-money options can be used as a model independent measure of implied volatility. This method effectively aggregated and averaged the implied volatility measure for all options into one implied volatility estimate for each underlying asset, even those with large skews. This method is the basis for listed volatility-based products, like VIX and is now commonly used in studies of the VRP. A CBOE White Paper [CBO 14] describes the calculation with a detailed example[2].

2 The general formula for the implied volatility measure used for both volatility swaps and VIX is: $\sigma^2 = \frac{2}{T}\sum_i \frac{\Delta K}{K_i^2} e^{RT} Q(K_i) - \frac{1}{T}\left[\frac{F}{K0} - 1\right]^2$, where:
T = time to expiration
F = the forward underlying spot level derived using option prices
K_0 = the first strike below the forward spot level, F
K_i = the strike price of the out of the money option. This is a call if $K_i > K_0$, a put if $K_1 < K_0$ and both if $K_1 = K_0$
$\Delta K_i = \frac{K_{i+1} - K_{i-1}}{2}$
R = risk free interest rate
$Q(K_i)$ = midpoint of the bid-ask spread for each option with strike K_i.
The CBOE S&P 500 volatility index (VIX) is a constant 30 day implied volatility index that uses a weighted average of the above equation with an expiration date shorter than 30 days and another with an expiration date longer than 30 days.

The realized volatility component of the VRP is the realized standard deviation of daily returns over approximately the same time period as the options used in the implied volatility calculation and is typically measured as follows, where *N* is the number of price data points and *Ln* is the natural log.

$$100 \times \sqrt{\frac{252 \times \sum_{t=1}^{N}\left(Ln\frac{P_t}{P_{t-1}}\right)^2}{\text{Expected } N}}$$

Note that the realized volatility is not the usual calculation for the standard deviation. Instead of calculating the squared deviations from the mean, the formula above uses the squared deviations from zero. The rationale for this measure is best illustrated by a simple example. If the S&P 500 was up exactly 1% for 12 months in a row, the typical standard deviation calculation would return a volatility of zero. Most investors would likely view any S&P 500 return other than zero as having some volatility and so for this reason the realized volatility calculation uses 0 instead of the sample mean.

14.3. Why does it exist?

The VRP has demonstrated a long-run persistent payoff to investors that maintain a consistent "short volatility" position. To bolster this argument, papers by Carr and Wu [CAR 09], Bates [BAT 00] and others have noted the fact that implied volatility is consistently higher than realized volatility. The premium can be viewed by sellers of volatility as compensation for the risk of losses when realized volatility increases sharply. Such periods tend to coincide with turmoil in the underlying market, elevated uncertainty and investor stress. Option implied volatility is consequently a biased estimate of future volatility – similar in some ways to the credit markets in which the credit-risk premium causes market implied default rates to exceed realized default rates, on average and compensates investors for the risk of losses on defaults and downgrades.

In a world in which investors could replicate options perfectly by delta hedging, such a premium would not exist. An arbitrager could, for example, sell an overpriced option and hold a delta-adjusted position in the underlying security, which in theory is a risk-less position. A sufficient number of such arbitrages should in theory drive the VRP to be close to zero. However, delta hedging requires trading the underlying frequently in an effort to mimic the payoff of the option. Generally, any realized volatility of underlying asset returns that are different than what was expected will increase the riskiness of delta hedging. This risk will take the form of increased tracking error between the hedging portfolio and the return of the option being replicated. Since volatility is actually stochastic, any large changes in realized volatility will increase the risk to delta hedging and sellers of volatility will naturally require higher returns as compensation for bearing this risk.

14.4. Evidence from CBOE Indices on VRP

A short volatility position that captures the VRP can generate significant risk-adjusted performance. The longest running indices with significant VRP exposure are the BXM and PUT Indices disseminated by CBOE. A more recent option index, the CNDR or Iron Condor Index, has more direct VRP exposure than does PUT or BXM. The BXM and PUT Indices have significant equity exposure while CNDR has very little. The reduced equity exposure in CNDR means that the returns to CNDR are more the result of exposure to volatility than are the returns of BXM or PUT.

The BXM Index represents passive exposure to a 1-month near-money covered call strategy. BXM buys 100 theoretical shares of the S&P 500 and sells a 1-month S&P 500 call with the first listed strike above the spot price. The PUT Index represents passive exposure to a 1-month near-money cash secured put strategy. PUT sells a 1-month S&P 500 near-money put with the first listed strike below the spot price and buys T-Bills approximately equal to the strike price of the put. The PUT strike is generally one strike lower than the BXM strike and both indices are rebalanced every month on the regular expiration date (the third Friday of each month). Interestingly, both strategies have an average beta of about 0.60, so the index returns are a combination the equity risk premium and the VRP.

In the absence of the VRP, the option associated with either the BXM or the PUT Index would have fair value. In other words, neither one of these indices would be expected to have any risk-adjusted alpha. Given their respective market exposures, the returns to the strategies should be approximately equal to a portfolio consisting of 60% S&P 500 and 40% of 1-month US T-Bills. From the standpoint of option theory, the BXM and PUT Indices should have similar returns, as a covered call position is identical to a cash-secured put position, but there are meaningful differences in the performance of these indices. Most of these differences can be attributed to dissimilar equity risk premium exposure on the single rebalance day of each month.

The CNDR Index consists of selling a passive put spread and call spread and investing in 1-month T-Bills. Each spread is rebalanced monthly on the regular expiration date. The short put has a delta of 0.20 and the short call has a delta of –0.20. The long put in the put spread has a delta of –0.05 and long call has a delta of 0.05. The net delta of the put spread is +0.15 and the net delta for the call spread is –0.15, such that the entire condor strategy starts delta-neutral. Given the construction of this index, its returns are driven primarily by the VRP, and it would be expected to have a relatively low beta with respect to the equity market. Over shorter periods of time, because the index is only delta neutral at the time the spreads are sold it can have some market exposure.

The performance of these indices is shown in Table 14.1. All three of these indices have generated returns in excess of their beta with respect to the S&P 500 Index. As expected, all three indices have economically meaningful alphas, although the over the time period in question the alphas associated with the BXM and CNDR are not statistically significant at 5%. The presence of the S&P 500 option skew is evidenced in a small part of the outperformance of the PUT Index over BXM, as they both involve similar 1-month positions but PUT is struck one strike lower than BXM. Despite the construction of the CNDR Index to have no market exposure at the inception of the positions, the strategy does have meaningful market exposure. Part of this exposure likely stems from the negative correlation observed between market direction and realized volatility – spikes in volatility that result in negative returns to the CNDR Index are also associated with declines in the market that results in a positive put spread delta. Table 14.1 shows the results of regression equations that remove the effect of the equity market (S&P 500) from the index returns. The constant term or alpha represents the remaining value-added factors. The largest remaining factor is likely to be volatility.

	S&P 500 Index	**BXM Index**	**PUT Index**	**CNDR Index**
Annualized Excess Return	6.42%	4.93%	6.25%	3.27%
Annualized Risk	14.44%	10.36%	10.00%	7.01%
Statistical Beta (*t* stat)	1	0.63 (32.16)**	0.57 (25.71)**	0.15 (5.90)**
Statistical Alpha (*t* stat)	0	0.80% (0.82)	2.49% (2.20)*	2.39% (1.82)

* Statistically significant at 5% (two-tail, +/-1.960)
** Statistically significant at 1% (two-tail, +/-2.576)

Table 14.1. *Performance of CBOE Indices January 1990 – December 2016*

While these indices and similar strategies have significant exposure to the VRP, they also have exposures to other factors such as market direction and interest rates. As such they are not ideally suited for an investor who is looking for pure exposure to the VRP. We now turn to the different ways in which investors can gain exposure to the VRP.

14.5. Trading the VRP

Many assets have exposure to volatility. Derivative instruments such as options and futures allow investors to hedge or take advantage of changes in volatility. Futures only have direct exposure to price movements, but systematic trading strategies such as delta hedging can be used to create option like payoffs using futures contracts. Options have natural exposure to the underlying instrument (stock, bond, currency, etc.) known as delta, exposure to interest rates known as rho, exposure to time known as theta and exposure to volatility known as vega. Neither options nor futures have pure exposure to volatility in that they are associated with other types of exposure. Using one of these instruments to capture the VRP requires that the investor take steps to manage or eliminate the other types of embedded risk exposures.

The purest way in which to capture the VRP is through the VRP derivatives available in the OTC market. These are volatility and variance swaps, with variance swaps the far more actively traded contract. The payoff to variance swaps is calculated as the difference between the annualized realized variance and the annualized variance strike, multiplied by the swap notional. This swap notional is also sometimes referred to as the vega notional, as it represents the gain or loss associated with a unit change in volatility.

The swap strike or initial implied uses the model independent calculation that is a weighted sum of all out of the money options (DDKZ) that have the same average expiration as the swap. As discussed above, this weighted sum is effectively an average implied volatility incorporating the skew into the calculation. The realized variance or standard deviation is then calculated over the contract period. Note that the payoff of the volatility swap (realized minus implied) contain the same components of the VRP definition, but in reverse order. Therefore, we will use the concept of a short position in a volatility swap to estimate the return to VRP.

Besides the advantage of pure exposure to the VRP, the swap returns are also very easy to calculate. In Table 14.2, we show an example of a term sheet for an S&P 500 volatility swap. Note that the payoff to the swap is purely a function of the difference between the realized volatility and the volatility strike, and has no dependence on the multitude of other factors that can, for example, affect the price of an option with similar maturity. The numerical difference between these two measures of volatility is then multiplied by 100 to convert into volatility points and then multiplied by the vega notional to determine the total amount that changes hands at the end of the swap transaction. For example in Table 14.2 the vega notional is defined to be $250,000. So if the realized volatility minus the implied volatility or volatility strike price was 3% (or +3 volatility points) over the life of the contract, the payoff to long contract holder would be \$750,000 and the short contract holder would owe \$750,000.

Swap details	Overall trade
Underlying Ticker	SPX
Client Direction	Short
Deal Number	NA
Counterparty	XXXXXXXX
Credit Code	NA
Collateral (vol points)	2.00
Collateral (\$)	\$500,000
Structure	Volatility Swap
Settlement Method	Cash
Trade Date	Wed, 20-Jan-2016
Initial Settlement Date	Fri, 22-Jan-2016
Settlement Convention	T+2
Maturity Date	Fri, 15-Dec-2017
Final Settlement Date	Tue, 19-Dec-2017
Currency	USD
Vega Notional	\$250,000
Volatility Strike Price	24.00
Expected N	482

Definitions	
First Observation	Trade Date
Last Observation	Maturity Date
Expected N	The actual number of Scheduled Trading Days that are not Disrupted Days during the Observation Period
P_t	The daily closing price of the index on each day during the Observation Period except on the Final Valuation Date, when Pt shall equal the SQ (futures settlement)
Final Realized Volatility (FRV)	$100 \times \sqrt{\dfrac{252 \times \sum_{t=1}^{N} \left(Ln\frac{P_t}{P_{t-1}}\right)^2}{Expected\ N}}$
Equity Amount	Vega Notional × [FRV – Volatility Strike]

Table 14.2. *Example term for S&P 500 volatility swap*

The cash flows associated with this type of swap transaction are different from those typically associated with the purchase and sale of an investment. Only collateral changes hands on the day the swap is bought or sold. The collateral is usually a function of the duration of the contract but is typically two volatility points multiplied by the vega notional. As is seen in Table 14.2, the collateral calculation would be the two volatility points multiplied by the vega notional or $500,000, equaling $1 million. Other than the requirements dictated by the initial collateral allocation, the amount of exposure is up to the investor. The scaling of the trade is an exercise in risk management, as the volatility of the trade can be adjusted by simply increasing or decreasing the amount of vega notional associated with the trade. This makes the concept of capital or cash invested meaningless as the investor can now choose to set aside any amount of cash against the swap contract.

14.6. Data construction

Return estimates from exploiting the VRP requires measures of future volatility and contemporaneous measures of implied volatility. These two parameters can then be combined to estimate the return to a volatility swap as described in the previous section.

We use three types of price data to measure realized volatility. For all commodity and fixed-income series, daily closing prices of the front month futures were used to calculate daily returns. All futures were assumed to be rolled on the day before first notice date. For the equity series, daily closing prices for each of the indices were used to calculate daily returns. Finally, daily returns for the currency series were calculated using the daily closing price of the relevant currency pair spot rate from the Bloomberg currency database. They consist of spot rates from bank foreign exchange trading desks sampled by Bloomberg. The realized volatility series for each asset was calculated as the annualized standard deviation of daily log returns over 22-day periods or approximately 1 month. As mentioned above, the standard deviation was calculated by substituting zero for the sample mean.

Implied volatility data were also obtained from Bloomberg. The most desirable measure of implied volatility for the purpose of investigating the payoff to VRP would be the volatility measure implicit in pricing the derivatives with pure exposure to volatility. This measure, derived by DDKZ, is calculated by appropriately weighting all out-of-the-money options. The methodology also has the advantage of being independent of any model assumptions such as the log normality of asset returns. Unfortunately the DDKZ requirement of employing all out-of-the-money options in the calculation is problematic for those asset classes that have less liquid options at some strikes. As a result, we chose to use the at-the-money series from Bloomberg as a conservative alternative. The at-the-money implied volatility is generally conservative because it does not capture the presence of option skew, where in most option markets the implied volatilities increase as the strike prices decrease. In some asset classes such as currencies, the implied volatility increases for strikes both higher and lower than the spot price.

The data set used to examine the premia across assets uses real market data from December 31, 2005 through June 7, 2016. For equity, fixed-income and commodity-related assets, the implied volatility series is computed as the average of the call and put implied for the at-the-money option of the first listed expiry at least 20 business days from the date under consideration. For currencies, the implied volatility series was defined to be implied volatilities sampled from the currency trading desks at banks.

The particular assets selected for use in this study are shown in Table 14.3, along with the associated VRP over the entire time period. These 20 three series were chosen because the underlying was actively traded and they had relatively active and liquid options markets. Note that the assets considered vary in terms of the types of risks to which they are exposed. For example, agricultural commodities such as wheat and corn have less exposure to economic cycle, which is not the case with equity-related indices or crude oil. Table 14.3 also includes information about the return distributions for each VRP. The columns on the far right show that nearly all VRP distributions are negatively skewed and that most have very fat tails. For these reasons, we have decided to use the median as the central tendency rather than the mean.

Exposure	**Bloomberg Ticker**	**Implied Volatility**	**Realized Volatility**	**VRP Mean**	**VRP Median**	**VRP Standard Deviation**	**VRP Skewness**	**VRP Kurtosis**
Commodity Coffee	KC1 Comdty	34.4%	30.2%	4.2%	4.6%	8.3%	-0.9	4.4
Commodity Corn	C 1 Comdty	31.0%	28.9%	2.1%	2.6%	7.9%	-0.3	1.0
Commodity Gold	GC1 Comdty	19.7%	18.8%	0.9%	1.1%	5.8%	-1.1	5.8
Commodity Natural Gas	NG1 Comdty	49.8%	45.4%	4.4%	4.1%	12.6%	0.1	3.8
Commodity Soybean	S 1 Comdty	25.4%	23.1%	2.3%	2.7%	6.2%	-0.4	1.0
Commodity Wheat	W 1 Comdty	33.5%	32.3%	1.2%	1.7%	8.6%	-0.2	1.2

Commodity WTI Crude	CL1 Comdty	36.3%	33.6%	2.7%	3.6%	10.4%	-0.4	3.8
Currency EUR-GBP	EURGBP Curncy	8.2%	7.7%	0.5%	0.7%	1.7%	-0.3	1.8
Currency EUR-USD	EURUSD Curncy	10.1%	9.3%	0.9%	0.9%	2.1%	-0.4	2.1
Currency GBP-USD	GBPUSD Curncy	9.2%	8.5%	0.7%	0.8%	2.0%	-0.5	2.8
Currency USD-JPY	USDJPY Curncy	10.6%	9.7%	1.0%	1.4%	3.2%	-0.8	1.5
Equity Australia	AS51 Index	18.5%	16.7%	1.9%	2.4%	6.4%	-1.6	8.5
Equity Eurozone	SX5E Index	22.2%	21.6%	0.6%	1.9%	7.6%	-2.2	8.5
Equity France	CAC Index	21.6%	21.4%	0.1%	1.3%	7.6%	-2.4	10.2
Equity Germany	DAX Index	21.5%	20.8%	0.7%	1.9%	7.1%	-2.3	9.9
Equity Hong Kong	HSI Index	24.0%	22.3%	1.7%	2.5%	8.7%	-1.8	10.7
Equity Japan	NKY Index	23.7%	22.5%	1.2%	3.0%	10.0%	-2.2	11.7
Equity Netherlands	AEX Index	20.3%	19.4%	0.9%	2.2%	7.6%	-3.1	16.5
Equity Switzerland	SMI Index	17.2%	16.5%	0.7%	1.8%	7.3%	-2.4	11.0
Equity United Kingdom	UKX Index	18.2%	17.2%	0.9%	1.9%	6.8%	-2.5	12.8
Equity United States	SPX Index	18.0%	17.0%	1.0%	2.2%	7.4%	-3.2	16.6
Fixed Income US 10YR Note	TY1 Comdty	6.1%	5.7%	0.4%	0.5%	1.5%	-1.0	6.4
Fixed Income US Long Bond	US1 Comdty	10.7%	10.0%	0.7%	0.9%	2.3%	-0.4	3.4

Table 14.3. *Volatility risk premia in equity, fixed income, currency and commodity markets January 2006–May 2016*

The first question we address is whether the VRP is present across the majority of the assets included in this study. For each asset, we compute the VRP using daily data, and then compute the median levels of this VRP over the entire time period. The resulting premia are shown in Figure 14.1.

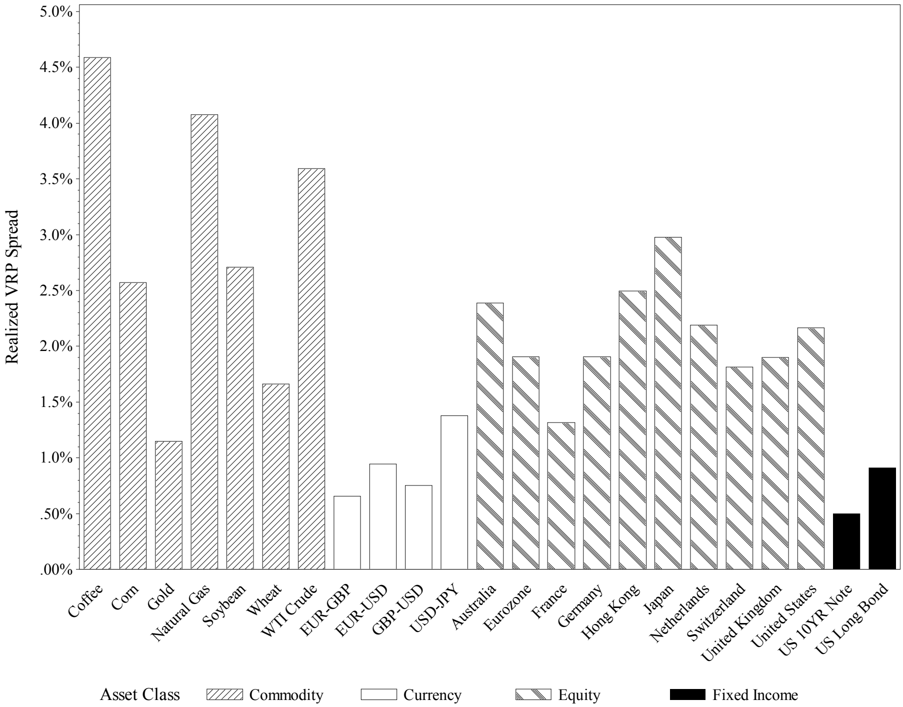

Figure 14.1. *Median VRP spread January 2006–May 2016*

Over this 10 year time period, the median spread is positive for all assets and varies from a low 0.50% for the 10 year US Treasury Notes to 4.5% for Coffee (or a 0.5–4.5 volatility point range). Commodities appear to be associated with the highest observed VRPs, and fixed income with the lowest levels. A positive VRP across all assets supports the view that the positive premia is not exclusive to equity options, but is an inherent return to investors who are willing to maintain a "short" position in the volatility of each of the assets. Maintaining a short position will expose the seller to losses when the volatility of the asset increases – a situation that is typically associated with increased uncertainty. The risk of a volatility spike and the hedging difficulties are not issues specific to any single asset or asset class; coffee, the EUR/USD exchange rate, the German stock index and the US 10-year note will all experience volatility spikes in the future and will likely be difficult to delta hedge.

The data in Figure 14.2 highlight another interesting VRP property. The magnitude of the VRP is positively correlated to the volatility of the underlying asset, and the correlation between realized VRP and realized volatility is 0.79. This could be a pure volatility effect or an asset class effect. By examining Figure 14.2 more closely, where each asset class is depicted with a different symbol, it can be seen that commodities are clustered together in the upper right corner, equity indices are mostly clustered in the middle and currencies and fixed income are together in the lower left corner of the scatter plot. This relationship between volatility and the magnitude of the risk premia is far less pronounced within asset classes. As seen in Figure 14.2, wheat, coffee, crude oil and corn have the similar realized volatility, but the observed VRPs vary from 1.66 to 4.59%.

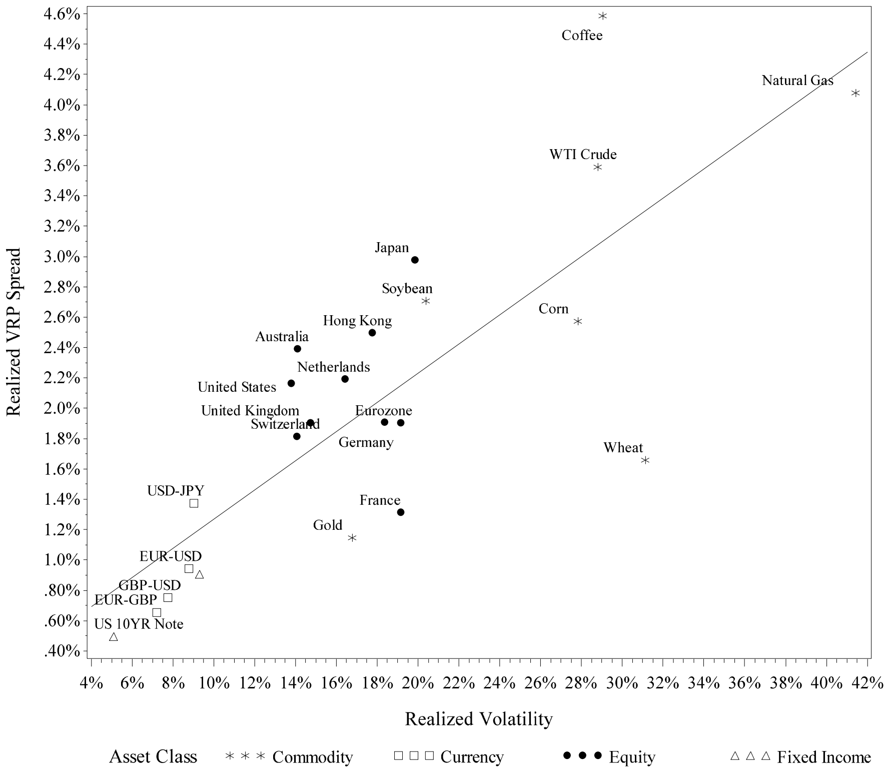

Figure 14.2. *VRP spread versus realized volatility January 2006–May 2016*

One way to adjust for this observed relationship to is to use the ratio of implied volatility to realized volatility as a measure of the VRP instead of the more popular arithmetic difference between implied volatility and realized volatility. The ratio measures implied volatility as a percent of the realized volatility so that now a two-volatility point difference between a 12% implied and 10% realized volatility spread will have the same impact to the portfolio as a six-volatility point difference between 36% implied and a 30% realized volatility spread.

Figure 14.3 graphs the median VRP ratio for all of the assets and grouped by asset class. This bar chart shows that the VRP ratio is more similar across assets and asset classes than was the VRP spread in Figure 14.1 and does not vary significantly by asset class. The average level of observed VRP ratio is 1.12 suggesting that option sellers generally require a premium of approximately 12% over the actual level of volatility as compensation for bearing the exposure to unexpected changes in volatility.

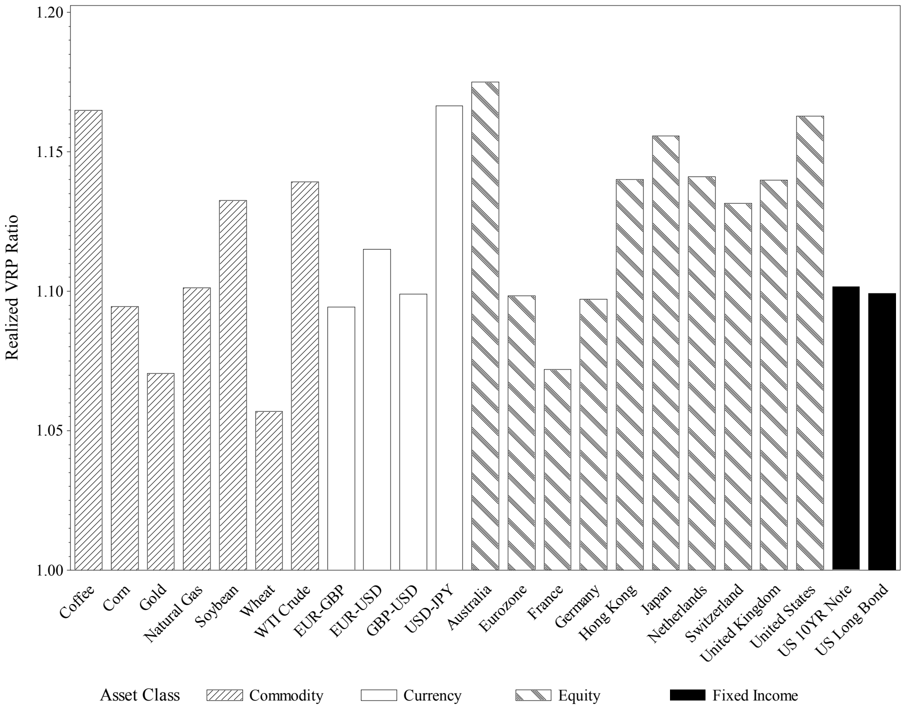

Figure 14.3. *Median VRP ratios January 2006–May 2016*

The lack of a systematic relationship between the VRP ratio and realized volatility is evident in Figure 14.4. We believe that by looking at the data in terms of a ratio, we can correct for the positive relationship bias between the size of the VRP and the realized volatility of the underlying asset. Figures 14.2–14.4 bolster the notion that the volatility premium may be driven by the volatility of the underlying asset.

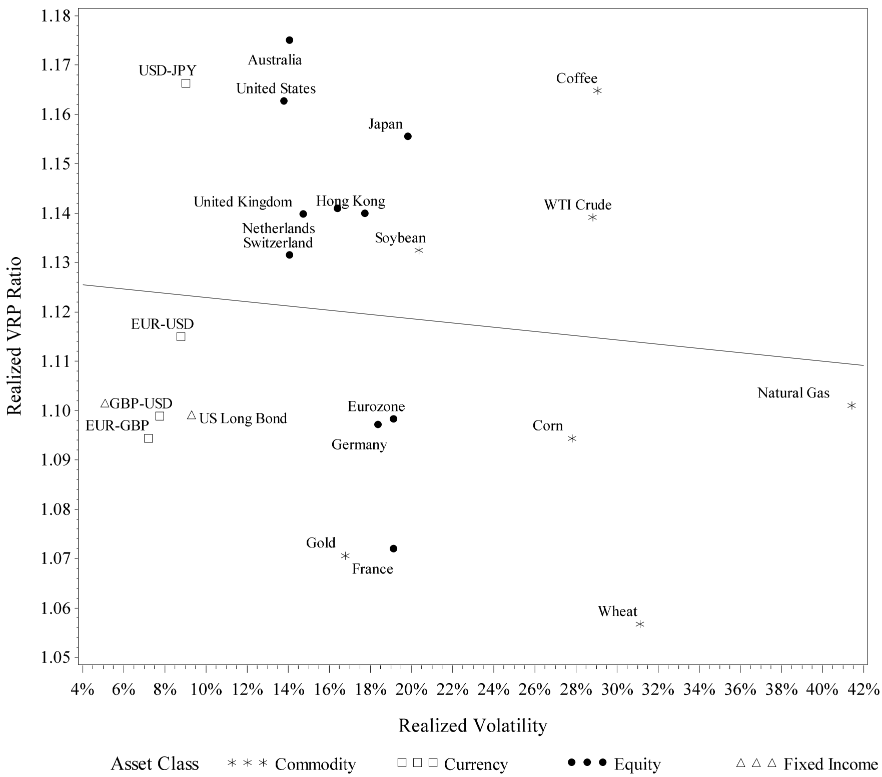

Figure 14.4. *VRP ratio versus realized volatility January 2006–May 2016*

Overall, these data suggest that the VRP is present globally, across asset classes and it is roughly the same size when adjusted for the volatility of the underlying security. In order to investigate whether this is due to the same macro sources of uncertainty, we next examine the correlations between these VRP ratios. At its core, the source of the VRP is uncertainty. Assets with high positive or negative correlation in returns arguably respond to the same sources of uncertainty, and we would expect the VRP of such highly correlated assets to exhibit higher levels of VRP correlation.

Given the wide range of assets used in this study, we observe a wide range in the correlations of VRPs ranging from a low of –0.10 to a high of 0.96. The best predictor of the correlation between VRPs is the correlation of the returns between the underlying asset returns. The higher is correlation of the asset returns – regardless of whether they are negative or positive – the higher is the correlation of the VRPs.

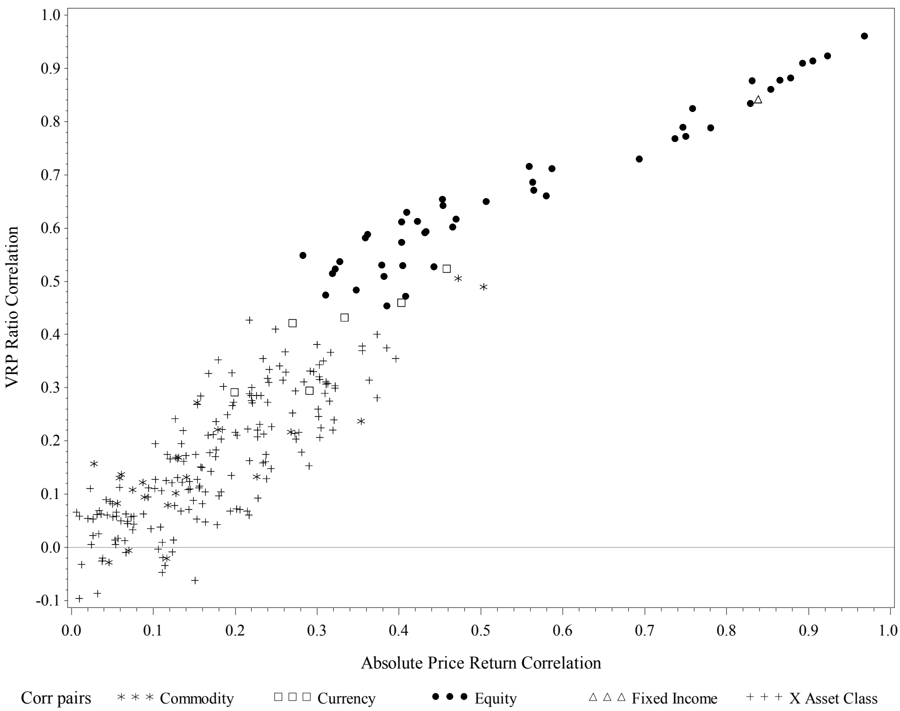

Figure 14.5. *VRP ratio correlation versus return correlation January 2006–May 2016*

Figure 14.5 shows the pairwise return correlations of all of the asset combinations in our VRP universe with the VRP correlations for the same pairs. The symbols on the graph other than the plus signs "+++" show these data for pairs in the same asset class. For example, the dots "•••" show the pairwise price correlations of the equity indices against the pairwise correlation of the VRP for the same equity indices. The plus signs "+++" shows the same calculation for assets not in the same asset class. For example, the pairwise price return correlation for the US dollar versus coffee is plotted against the pairwise VRP correlation for the same two assets. Note that once again the symbols have tended to cluster together. Equity dots have tended to cluster together on the right-hand side. Commodities have clustered on the far left and currencies in the middle. The strength of this relationship is depicted in Figure 14.5, where we plot the relationship between the correlations of the underling price returns and the correlation of the VRP ratio. The correlation between these two measures is 0.93.

This turns out to be a useful property when building portfolios containing volatility swaps in practice. Since the VRP data for volatility swaps may be limited for a large number of underlying assets and asset classes, this fact that the VRP correlation can be estimated using the price return correlation enables the construction of efficient portfolios of volatility swaps.

14.7. VRPs in a portfolio context

For risk management or asset allocation purposes, transactions involving swaps should be viewed in units of risk as opposed the notional contract value. For the purpose of defining position sizes for constructing portfolios in this study, we scaled VRP positions such that each return series has a 5% monthly standard deviation over the total time period. This means that the constant scale factor for each series has a look-ahead bias. This construction method was carried out to illustrate the characteristics of a portfolio of VRPs, and not an attempt to detail a process for constructing an investable portfolio.

Assets with monthly standard deviations greater than 5% had their returns de-levered and assets with a standard deviation less than 5% had their returns levered up such that the standard deviation of monthly returns for all assets equaled 5%. Such scaling allows direct comparison of the returns associated with the different types of VRP considered in this study. Note that the level of scaling of 5% on a monthly basis (or 17.3% on an annual basis) has no impact on the return per unit risk associated with the swap returns.

In Table 14.4, we show excess returns, risk and Sharpe ratios for diversified portfolios with exposure to VRP. There are six portfolios considered, and they were constructed without constraining the correlation of asset VRPs within the portfolio. For each asset class portfolio in Table 14.4, we construct a portfolio consisting of VRP positions that are equal-risk weighted within each asset class and then compute the returns to these four asset class portfolios. For example, the fixed-income VRP portfolio is constructed to have 50% risk allocation to the two fixed-income assets, where each VRP position is appropriately scaled to equal 5% monthly risk as described above. In addition, we also compute the returns to two other portfolios. While both these portfolios contain all the same securities, the allocation methodology used to construct them is different. In the series depicted as equal asset VRP, we allocate such that each of the 20 three underlying VRP positions has equal risk allocation. In the portfolio depicted as equal asset class VRP, we allocate the same amount of risk to each of the four asset class portfolios, and then allocate equal risk to each asset within each asset class. This means that while each asset class VRP portfolio contains an equal risk allocation to each asset VRP in that asset class, the equal asset class VRP portfolio now also allocates an equal amount of risk to each asset class portfolio. Because of the higher correlation expected within and across asset classes, we would expect the equal asset class portfolio to have a better risk-adjusted return.

	Equity VRP	Commodity VRP	Currency VRP	Fixed Income VRP	Equal Asset VRP	Equal Asset Class VRP
Annualized Excess Return	4.38%	13.45%	19.97%	17.38%	11.25%	14.17%
Annualized Risk	15.48%	9.72%	13.72%	16.25%	10.83%	10.47%
Sharpe Ratio	0.28	1.38	1.46	1.07	1.04	1.35

Table 14.4. *Risk and return of VRP portfolios January 2006–May 2016*

Not surprisingly, diversifying across assets and within an asset class increases the Sharpe ratio of the VRP portfolio by reducing the annualized portfolio risk below 17.3%, but in some cases the improvement is quite limited as in the case of fixed income. The annualized excess return of the fixed-income VRP portfolio is 17.38% with annualized risk of 16.25% resulting in an average Sharpe ratio of 1.07. The slight reduction in risk from the maximum 17.3% to 16.25% represents high correlation among the fixed-income assets and thus very little diversification within this portfolio. The portfolios that show a significant reduction in risk are those where the assets within the portfolio are relatively uncorrelated. For example, the annualized risk of the commodity VRP portfolio, constructed with seven assets whose annualized realized volatility of returns range from 18.8% to 45.4% (see Table 14.3), is considerably lower at 9.72% with an annualized return of 13.45%, resulting in a Sharpe ratio of 1.38. The equity VRP portfolio, which is best documented, has the lowest Sharpe ratio of 0.28, which strikingly is similar in magnitude to the S&P 500 equity risk premium.

In comparing the multiasset portfolios, the equal asset class VRP portfolio provides highest annualized excess return, but with the lowest risk. The annualized risk reduced from the maximum 17.3% to 10.47%, representing the low correlation within asset classes and across asset classes in this portfolio. As expected, the portfolio that is more diversified across asset classes has the higher Sharpe ratio, and it is this equal asset class VRP portfolio that is considered in subsequent analysis.

14.8. VRPs and PFPs

One of the advantages of including the VRP in a portfolio is gaining exposure to a return pattern, which is uncorrelated with the common factors that affect more traditional asset classes. We now turn to examining the relationship between the

VRP and six PFPs, which were constructed to capture either the prevailing inefficiencies or risk premia in equity markets. Specially, we will measure the VRP portfolio's relationship to the equity market, value, momentum, small size, low beta, profitability and bond beta.

The PFPs used in this section are described in detail in a paper by Clarke *et al.* [CLA 17]. A PFP is an investable portfolio that is rebalanced monthly and that has a near one standard deviation exposure to the factor in question and no exposure to the other pure factors. The monthly returns and factor exposures were calculated using 1,000 large US stocks for the 50 years ending 2016. The return to a PFP can now be thought of as the return to only that single factor.

In Table 14.5, we show the relationship between our VRP portfolios and the six PFPs. Not surprisingly, the equity VRP portfolio has greatest amount of variability explained by the PFPs, as evidenced by the regression R square of 0.55. The equity VRP portfolio has statistically significant positive exposure to the market return and momentum, and it has statistically significant negative exposure to value and bond returns. The commodity VRP portfolio, with an R square of 0.14, is not significantly related to any of the PFP returns except the low beta factor. The low beta coefficient of –0.57 is significant at the 5% level and it is economically large. The bond beta coefficient of –0.43 is nearly significant with a *t*-stat of –1.85. The currency VRP regression has an R square of 0.19 and none of the PFP coefficients are statistically significant. Similarly, the fixed-income VRP portfolio regression has an R square of 0.18 and only the market PFP coefficient is significant.

The intercepts of regressions in Table 14.5 represent a multifactor Jensen's monthly alpha. All the single asset class VRP portfolios have statistically significant positive intercepts over 1% except for the equity portfolio. This means that the commodity, currency and fixed-income VRP portfolios have strong positive returns after controlling for the effect of other common equity factors. The alpha associated with the equity VRP portfolio is not statistically significant and near zero. This highlights the importance of a portfolio selection process that carefully selects attractively priced equity VRPs that have strong positive payoffs, such as the S&P 500 or the Australian S&P/ASX 200 Index.

Finally, the return and diversification benefits of the individual single asset class building blocks of the equal asset class VRP portfolio support the attractiveness of a multiasset VRP portfolio. The equal asset class VRP portfolio has a very statistically significant monthly alpha of 0.89%, or 10.68% per year, net of all the other PFP exposures. The market coefficient and the value coefficient are both statistically significant while the remaining factor coefficients mostly have *t*-stats above 1.0. This shows that a portfolio of VRPs weighted using a passive process can have significant and consistent returns, net of the other common equity factors. A diversified VRP portfolio will be a good source of risk-adjusted value added when included in most portfolios.

$$\begin{aligned} VRP\ Portfolio = {} & Intercept + Coeff_{Market} \times \boldsymbol{Market} + Coeff_{Value} \times \boldsymbol{Value} \\ & + Coeff_{Momentum} \times \boldsymbol{Momentum} + Coeff_{Small\ Size} \times \boldsymbol{Small\ Size} \\ & + Coeff_{Low\ Beta} \times \boldsymbol{Low\ Beta} + Coeff_{Profitability} \times \boldsymbol{Profitability} \\ & + Coeff_{Bond\ Beta} \times \boldsymbol{Bond\ Beta} + \varepsilon \end{aligned}$$

	Equity VRP	**Commodity VRP**	**Currency VRP**	**Fixed Income VRP**	**Equal Asset Class VRP**
R Square	0.55	0.14	0.19	0.18	0.41
Intercept (*t* Stat)	-0.04 (-0.13)	1.13 (4.36)**	1.44 (4.08)**	1.03 (2.45)*	0.89 (3.86)**
Market (*t* Stat)	0.61 (6.31)**	-0.01 (-0.09)	0.19 (1.63)	0.42 (3.06)**	0.30 (4.03)**
Value (*t* Stat)	-0.99 (-2.11)*	0.18 (0.43)	-0.71 (-1.27)	-1.35 (-2.04)*	-0.72 (-1.98)*
Momentum (*t* Stat)	0.53 (2.35)*	-0.05 (-0.27)	-0.05 (-0.17)	0.39 (1.22)	0.20 (1.17)
Small Size (*t* Stat)	0.52 (1.61)	0.32 (1.13)	0.15 (0.39)	0.63 (1.39)	0.41 (1.62)
Low Beta (*t* Stat)	-0.35 (-1.26)	-0.57 (-2.37)*	-0.59 (-1.79)	0.12 (0.30)	-0.35 (-1.62)
Profitability (*t* Stat)	0.13 (0.33)	-0.29 (-0.86)	0.06 (0.12)	0.34 (0.62)	0.06 (0.19)
Bond Beta (*t* Stat)	-0.55 (-2.05)*	-0.43 (-1.85)	-0.38 (-1.20)	0.03 (0.07)	-0.33 (-1.61)

* Statistically significant at 5% (two-tail, +/-1.960)
** Statistically significant at 1% (two-tail, +/-2.576)

Table 14.5. *Regression of portfolio excess returns on pure factor portfolios January 2006–May 2016*

The multivariate regression analysis is on monthly excess returns and factor exposures on 1,000 large US stocks for the 50 years ending 2016. Six pure factor portfolios, value, momentum, small size, low beta, profitability, and bond beta, were constructed as described in [CLA 17].

It should be noted that the PFPs were developed to explain the cross-section of equity returns. As such it may not be surprising that they have little power in explaining non-equity volatility risk premia. A better way to analyze VRP returns for asset classes other than equities would be to use systematic factors that are specific to each asset class. Although given the power of PFPs in explaining equity and fixed-income market behavior, it would be fair to conclude that VRPs represent a unique source of returns to an investor's portfolio. As with other investment strategies there also appears to be a gain to diversifying VRP exposure across unrelated underlying assets to increase risk-adjusted return. While identification of uncorrelated VRPs may be difficult given the dearth of historical data on VRPs, the relationship between the returns of the underlying assets appears to be an adequate proxy for this purpose.

14.9. Conclusion

The VRP exists within and across asset classes and through time. The VRPs of assets within an asset class seem to be relatively correlated to each other but uncorrelated to VRPs in other asset classes. The relationship between the VRP and the volatility underlying asset is positive, and converting the premia relationship into a ratio removes this bias. The data also suggest the VRPs examined in this chapter are not related to the standard equity market factors represented by the PFP returns. Thus, VRPs appear to be a "new" or "different" source of risk premia.

These characteristics make adding a VRP component to an investment portfolio attractive. Exploiting the VRP can be done by using a variety of derivative instruments such as options, futures and variance and volatility swaps. Gaining VRP exposure through derivatives that do not require a significant cash allocation means that VRP exposure can by overlaid on virtually any asset portfolio. The most direct way to include exposure of the VRP to a portfolio is through volatility and variance swaps. Another attractive way to add VRP exposure to a portfolio would be by hedging long asset exposure in a portfolio by selling covered calls. Covered call writing would not only reduce the underlying asset exposure, but it would add alpha by additionally shorting volatility. VRP exposure is gaining momentum among asset owners as a way to add a significant source of relatively uncorrelated value to almost any investment portfolio. The findings presented here make a strong case for including VRPs as an additional source of return, but investors should be careful to recognize the additional market risk associated with making such an allocation.

14.10. Bibliography

[BAK 03] BAKSHI G., NIKUNJ K., "Delta hedged gains and the negative market volatility risk premium", *Review of Financial Studies*, vol. 16, no. 2, pp. 528–566, 2003.

[BAT 96] BATES D., "Testing option pricing models", in MADDALA G.S., RAO C.R. (eds.), *Handbook of Statistics 14: Statistical Methods in Finance*, Elsevier, Amsterdam, 1996.

[BAT 00] BATES D.S., "Post-'87 crash fears in the S&P 500 futures option market", *Journal of Econometrics*, vol. 94, nos. 1–2, pp. 181–238, 2000.

[BLA 73] BLACK F., SCHOLES M., "The pricing of options and corporate liabilities," *Journal of Political Economy*, vol. 81, pp. 637–654, 1973.

[BRE 78] BREEDEN D., LITZENBERGER R., "Prices of state-contingent claims implicit in option prices", *Journal of Business*, vol. 51, pp. 621–651, 1978.

[CAR 09] CARR P., WU L., "Variance risk premium", *Review of Financial Studies*, vol. 22, no. 3, pp. 1311–1341, 2009.

[CBO 14] CBOE WHITE PAPER, The CBOE Volatility Index – VIX, White Paper, available at: https://cboe.com/micro/vix/vixwhite.pdf, 2014.

[CLA 17] CLARKE R., DE SILVA H., THORLEY S., "Pure factor portfolios and multivariate regression analysis", *Journal of Portfolio Management*, vol. 43, no. 3, pp. 16–31, 2017.

[DEM 99] DEMETERFI K., DERMAN E., KAMAL M. *et al.*, "A guide to volatility and variance swaps", *Journal of Derivatives*, vol. 6, no. 4, pp. 9–32, 1999.

[DUA 07] DUARTE J., JONES C.S., "The price of market volatility risk", *SSRN Electronic Journal*, available at: https://dx.doi.org/10.2139/ssrn.1106960, 2007.

[FAL 15] FALLON W., PARK J., YU D., "Asset allocation implications of the global volatility premium", *Financial Analysts Journal*, vol. 71, no. 5, pp. 38–56, 2015.

[GE 16] GE W., "A survey of three derivative based methods to harvest the volatility premium in equity markets", *Journal of Investing*, vol. 25, no. 3, pp. 48–58, 2016.

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15

Factor Investing and ESG Integration

We examine the relationship between Environmental, Social and Governance (ESG) metrics and risk factors and the impact of ESG integration on different investment strategies through a consistent portfolio construction framework. We find that ESG generally improved the historical risk-adjusted performance of many typical passive and factor investment strategies and tilted the original strategies toward larger companies with higher profitability, more stable earnings, lower leverage and lower volatility. We also show that the impact of ESG integration on target factor exposure and therefore on the *ex ante* information ratio (IR) was relatively modest and varied according to the primary objective and target factors of the underlying strategies.

15.1. Introduction

In the past 10 years, ESG considerations have increasingly become integrated into mainstream portfolio management. A large number of long-term institutions such as pension funds, sovereign wealth funds, insurance companies, endowments and foundations have signed up to the UN Principles for Responsible Investment[1]. Many of these institutions either make allocations to segregated ESG mandates or incorporate ESG criteria across their entire portfolio. Asset managers have responded to this increasing demand from asset owners and have started to integrate ESG into their strategies using mechanisms ranging from exclusions based on screening to full integration into the security selection and portfolio construction process.

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1 As of April 2016 1,500 financial institutions with total assets in excess of $60 trillion had become signatories of the Principles for Responsible Investments (PRI). Further information can be found on www.unpri.org.

The integration of ESG criteria into long-term portfolios raises many important empirical questions. What is the impact of ESG on portfolio performance? How does it change the risk profile and the factor exposures of portfolios? How does it affect the ability of different investment strategies to pursue their investment objectives? Are passive strategies able to capture the broad equity market return? Are factor strategies able to maintain appropriate exposure to their target factors? We use a consistent portfolio construction framework to investigate how ESG integration affects different investment strategies and provide answers to these questions.

We start by analyzing the properties of ESG scores and their relationship with traditional equity factors and find that ESG has a positive correlation with size, quality and low volatility. Then, we assess the impact of ESG integration on passive investment strategies. Our results show that incorporating ESG into passive strategies had a positive impact on risk-adjusted performance over the period 2007–2016. Benchmarks that reweight the constituents of the MSCI World Index toward companies with high and improving ESG ratings achieved Sharpe ratios in line with the parent index. Optimized index tracking portfolios that maximized ESG exposure subject to an active risk constraint achieved consistently positive information ratios.

ESG integration generally improved the historical performance of the factor strategies we evaluated. More importantly, adding ESG did not restrict substantially the exposure of these strategies to their target factors and therefore their ability to fulfill their primary investment objective. The impact of ESG integration varied according to primary objective and target factors. For example, minimum volatility strategies experienced only a 7% reduction in target factor exposure for a 30% enhancement in ESG rating. On the other hand, value strategies incurred a 22% reduction in target factor exposure for a similar 30% improvement in their ESG characteristics.

This analysis has implications for passive investing, factor investing (smart beta) and active portfolio management. Passive strategies with enhanced ESG characteristics were able to capture market returns efficiently. Factor strategies and active portfolios could have enhanced their ESG profile without impairing their ability to pursue their primary investment objective. Defensive strategies in particular, such as high quality and low volatility, were able to maintain high exposure to their target factors as ESG scores had a positive correlation with these factors. Even dynamic strategies such as those based on the value and momentum factors could have enhanced their ESG profile significantly with a relatively modest impact on target factor exposures and *ex ante* information ratios.

15.2. Data and methodology

Several studies address integration of ESG criteria into equity portfolios, focusing on the effects on company or portfolio performance. The majority of these studies report a positive relationship (see [FRI 15]). In recent years, some studies have also proposed explicit ways to integrate ESG criteria into a fundamental or quantitative investment process. Nagy *et al*. [NAG 13, NAG 15] have shown that in a classical quantitative portfolio construction framework, ESG data can be used to construct portfolios of various risk levels that are tilted toward better ESG-rated stocks or stocks with improving ESG ratings. Backtested results show these portfolios outperformed their benchmark. Similar results were found in other quantitative-oriented studies (see, for example, [JUS 13, HIT 15]). When it comes to passive factor investing products (smart beta products), initial results have also been positive. For example, a Northern Trust study showed that an ESG signal combined with a quality portfolio yielded additional outperformance [NOR 14].

In this chapter, we provide a systematic overview of the interaction between factor investing and ESG integration[2]. As these two structural trends continue into the future, the list of factors and strategies that investors would like to implement in a more sustainable way may become longer. We examine the implications of ESG integration beyond the realm of pure factor investing and assess the impact of ESG criteria on passive investing and active management in general using a bottom-up approach. We first look at stock–level relationships between familiar risk factors and ESG metrics. This analysis provides the necessary information about the interaction between ESG and factors. We then move to portfolio-level analysis and assess the potential effects of ESG constraints on different passive and active strategies.

We use the constituents of the MSCI World Index as the basis of our analysis. The MSCI World Index constituents represent the largest and most liquid stocks in global developed equity markets. For a list of globally relevant risk factors, we turn to the MSCI Global Equity Model for Long Term Investors (GEMLT) that contains 16 well-established style factors based on fundamental or technical stock characteristics that are significant drivers of price movements and correlations[3]. Technical factors in GEMLT include beta and momentum, while fundamental factors include size, value, dividend yield and several aspects of quality. These factors encompass relevant systematic risk drivers identified by practitioner and academic research, and also incorporate many factors that investors use in alpha

2 For a discussion of the role of factor investing in institutional portfolios, see [MEL16].

3 For a full list of factors and more details on the MSCI Global Equity Model, see [MOR 15].

models to harvest return premia, known as Systematic Equity Strategy (SES) factors[4].

To analyze the ESG tilts of portfolios, we use the MSCI ESG ratings data set. These data are derived by identifying key issues by industry, determining their relative importance and assigning weights to them accordingly. Each company is then assigned a score ranging from 0 to 10 based on how much exposure it is deemed to have to the relevant key issues. Exposure scores are aggregated into the three pillar scores (Environment, Social, Governance) and the weighted average key issue score. The final score is adjusted by industry; it thus describes each company's ESG performance relative to its industry peers[5].

The chapter is organized as follows. We start by reviewing the relationship between ESG and other familiar risk factors in the context of a fundamental factor model. Then, we analyze the impact of ESG integration on three broad classes of investment strategies: passive strategies, defensive strategies and dynamic strategies. Finally, we summarize our findings and show the tradeoff between ESG profile improvement and the impact on target factor exposure for all the strategies we investigated.

15.3. Treating ESG as a factor

Investors generally view ESG as a consideration in their portfolio management process and not necessarily as a traditional systematic risk factor. Nevertheless, at the technical level, ESG data can be integrated into the framework of equity factor models as a potential new factor. Since companies are assigned numerical ESG scores, they can be easily transformed into exposures (i.e. z-scores) that form the basis of factor models. By putting ESG on an equal footing with other factors, we can subject it to a series of standard tests to evaluate its strength and relevance as a systematic factor.

First, we create monthly rebalanced equally weighted decile portfolios by sorting stocks by their ESG exposure and compare their performance relative to the equally weighted opportunity set (MSCI World Index constituents) over the period January 2007–June 2016. As we can see in Figure 15.1, better-rated deciles did not

4 For more information on SES factors and their use in active management, please see [BAL 16].

5 For more details on the ratings methodology, see [MSC 15].

systematically outperform worse-rated deciles. The best decile produced positive excess return but the intermediate deciles showed no clear trend.

Decile portfolio performance is a crude measure of factor strength, as it does not control for cross-sectional relationships between the analyzed factor and other factors. The next step is to evaluate ESG in a multivariate framework, i.e. examine its risk and return after controlling for the effects of other factors. Depending on what factors we use as control variables, we have two multivariate versions: one where we control for all the factors of GEMLT (denoted "all styles" in Figure 15.1) and one where we control for all but the style factors (denoted "single style" in Figure 15.1).

Chart 1.1

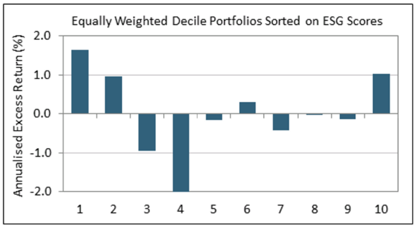

Chart 1.2

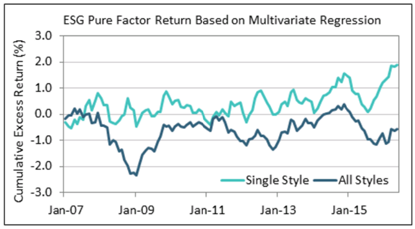

Table 1.1

Correlations	ESG	E	S	G
Mid Capitalization	-0.17	-0.19	-0.07	-0.04
Earnings Variability	-0.12	-0.12	-0.08	-0.10
Residual Volatility	-0.07	-0.07	-0.06	-0.11
Book-to-Price Ratio	-0.06	-0.08	-0.03	-0.07
Liquidity	-0.04	-0.03	-0.01	0.01
Leverage	-0.03	0.02	0.00	-0.03
Beta	-0.03	0.00	-0.02	-0.07
Growth	-0.02	0.00	-0.02	-0.02
Momentum	0.00	0.02	-0.01	0.03
Earnings Yield	0.01	0.01	-0.03	0.01
Earnings Quality	0.03	0.05	0.04	0.03
Long-Term Reversal	0.04	0.01	0.04	-0.03
Profitability	0.06	0.06	0.03	0.08
Dividend Yield	0.07	0.04	0.05	0.07
Investment Quality	0.08	0.09	0.05	0.05
Size	0.17	0.19	0.07	0.04

Table 1.2

Correlation T-stats	ESG	E	S	G
Mid Capitalization	-6.87	-7.59	-2.81	-1.65
Earnings Variability	-4.95	-4.62	-2.96	-3.99
Residual Volatility	-2.97	-2.65	-2.49	-4.46
Book-to-Price Ratio	-2.32	-3.09	-1.11	-2.63
Liquidity	-1.43	-1.24	-0.43	0.26
Leverage	-1.29	0.92	0.01	-1.03
Beta	-0.98	0.05	-0.77	-2.71
Growth	-0.87	-0.02	-0.88	-0.79
Momentum	-0.15	0.92	-0.38	1.34
Earnings Yield	0.31	0.56	-1.03	0.27
Earnings Quality	1.24	1.99	1.47	1.03
Long-Term Reversal	1.50	0.48	1.47	-1.08
Profitability	2.17	2.35	1.25	3.23
Dividend Yield	2.68	1.69	1.89	2.88
Investment Quality	3.17	3.36	1.78	2.07
Size	6.62	7.46	2.76	1.47

Figure 15.1. *ESG performance and correlations. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

Chart 1.2 in Figure 15.1 plots the return of the "pure" ESG factor in these settings[6]. There was no clear trend over this period, a similar conclusion to the decile

6 Pure factor portfolios are long-short portfolios that have unit exposure to a target factor, zero exposure to all other factors and minimum specific risk. They isolate the effects of a particular factor, net of all other factors. For a more detailed review of factor portfolios linked to the returns from multivariate regressions, see [MEL 10].

analysis. We also note that controlling for style factors subtracted from ESG factor performance. This result indicates that gaining exposure to ESG entails exposure to other style factors that deliver positive performance. Besides evaluating ESG factor performance, we look at its risk characteristics. Its statistical significance (measured by t-statistic) and volatility places it among the least volatile factors of the GEMLT model (with factors such as Growth or Earnings Quality) but without having a significant return associated with it[7].

We have seen that cross-sectional relationships with other factors influenced the performance of the stand-alone ESG factor. As a next step, we look at these important relationships in more detail. The simplest way to measure the dependency between factors and ESG scores at the individual stock level is via cross-sectional correlations of stock-level factor exposures with stock-level ESG scores. For completeness, we included similar measures for the three ESG pillar scores (Environment, Social, Governance). Tables 1.1 and 1.2 in Figure 15.1 show average correlations for the 16 style factors of GEMLT, while Figure 15.2 shows correlations through time for selected factors.

Two general observations can be drawn from these results. First, the average level of correlations between factors and ESG scores is low, i.e. ESG scores are a largely independent, new source of information, but we can still find some intuitive and statistically significant relationships. Second, the pillar scores have varying correlations with equity factors. While the level of correlation was generally low, many of those relationships were stable and significant over time. For example, we observe a positive correlation with the size factor and a negative correlation with the midcap factor. These observations both indicate that on average larger companies tended to have better scores. We also note that this relationship persisted at the pillar level but was strongest for the Environment pillar score and weaker for the Social and Governance scores[8].

7 In the univariate regression the ESG factor had annual returns of 0.20% and annual volatility of 0.88%, resulting in an information ratio of 0.22. In the multivariate regression the ESG factor had annual returns of –0.06% and a volatility of 0.74%. The mean absolute *t*-stats were 1.18 and 0.94, respectively. For comparison, over the same period, the multivariate earnings quality factor had annual returns of 0.27%, volatility of 0.92%, IR of 0.30 and t-stat of 0.97. So the ESG factor was similar to earnings quality in terms of statistical significance and performance.

8 The relationship between size and ESG has decreased somewhat since 2010. Large companies tended to disclose more ESG-related data. Easier access to data may have biased ESG scores in their favor. This initial potential bias has gradually been eliminated. A positive relationship between company size and ESG persists.

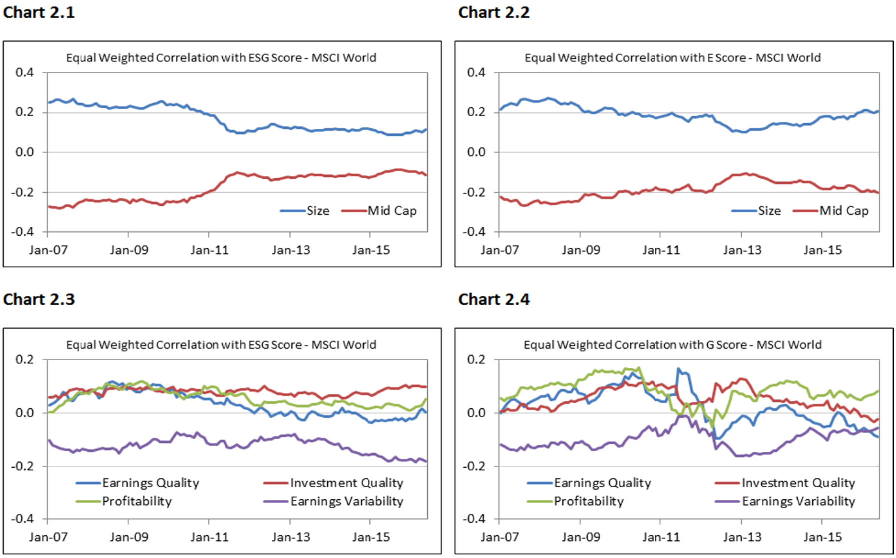

Figure 15.2. *Correlation between ESG and factors. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

We also observe a positive relationship between ESG scores and financial quality characteristics. Stocks with more stable earnings, lower accruals, higher profitability and better investment quality[9] tended to have better ESG scores. The correlation between profitability and the Governance pillar score is even higher, indicating a slightly stronger relationship between governance and profitability (see [LEE 15]). The positive connection between quality and ESG explains the difference in the factor return graph (Chart 1.2 in Figure 15.1). Better ESG stocks tended to be better quality stocks and quality has historically earned a premium. Thus, in a multivariate regression framework, controlling for the quality tilts mechanically entailed by the ESG tilt reduced the performance of the ESG factor.

We conclude this section by examining the distribution of ESG scores for selected countries and sectors and by assessing how quickly these scores change over time. Chart 3.1 in Figure 15.3 shows that European companies tend to have better ESG characteristics than their peers in Japan and in the United States. Chart 3.2 in Figure 15.3 confirms that there were no major biases in the way companies were assessed relative to their sector peers. Chart 3.3 in Figure 15.3 shows that ESG ratings experienced annual turnovers of 32%. Most changes were by one unit while

9 Better investment quality is defined as lower asset growth and higher share buybacks, see [MOR 15].

8% of the changes were by two units or more. Finally, Chart 3.4 in Figure 15.3 shows positive autocorrelations for up to 36 months suggesting that the information contained in ESG ratings, which are updated annually, tends to decay over a period of approximately 3 years.

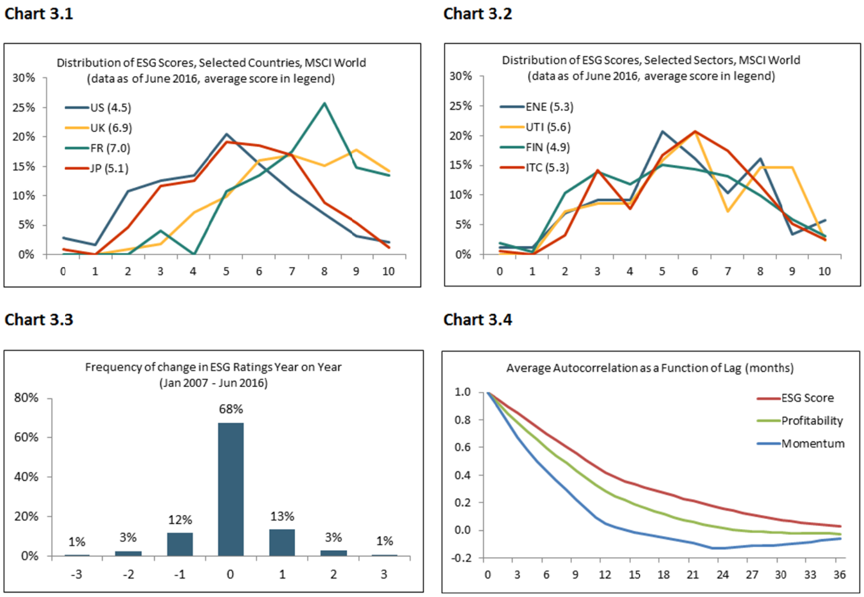

Figure 15.3. *Distribution of ESG scores and frequency of change. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

In this section, we analyzed the relationship between ESG and traditional risk factors and found that ESG had low but statistically significant positive correlations with quality and low-volatility factors. We also found that the correlation between ESG and other factors, such as value and momentum, tended to be zero or negative. Next, we assess the impact of ESG integration on different investment strategies. The correlation analysis suggests that ESG may have varying impact across strategies.

15.4. Integrating ESG into passive strategies

Investors are pursuing a range of strategies to integrate ESG analysis into their investment process[10]. Some asset owners have started to explicitly incorporate these

10 For example, see "Sweden's AP4 Shuns Fossil Fuels", Financial Times, 15 August 2016.

beliefs into their policy benchmarks. Other investors have explored overlays of ESG criteria into passive strategies. Finally, some investors have started to deploy factor-based or active strategies incorporating ESG. Regardless of strategy, investors share a common concern: does ESG integration impair or enhance the ability of each strategy to pursue its investment objective? In this section, we investigate the impact of ESG on index construction and then test a range of passive strategies incorporating ESG criteria.

To address the potential need for benchmarks that reflect ESG criteria, we investigate how the MSCI World Index could be modified to account for the ESG characteristics of its constituents. Specifically, we combine ESG ratings with market cap weights to derive "tilted" index weights. We examine three variants of this reweighting process. The first approach (ESG Level) is based only on current ratings and therefore rewards companies that have already achieved best-in-class. ESG performance. The second method (ESG Change) focuses on the change in ratings in the previous 12 months, emphasizing ESG improvement. Finally, the third method (ESG Tilt) combines current level and 12-month change. In all three approaches, the simulated strategies are rebalanced quarterly.

Table 4.1

Performance & Characteristics	MSCI World	ESG Level	ESG Change	ESG Tilt (Lev + Chg)
Total Return (%)	3.1	3.0	3.2	3.0
Total Risk (%)	17.2	17.1	17.1	17.1
Return/Risk	0.18	0.18	0.19	0.18
Sharpe Ratio	0.13	0.13	0.14	0.13
Active Return (%)	0.0	-0.1	0.1	-0.1
Tracking Error (%)	0.0	0.7	0.4	0.7
Information Ratio	NA	-0.15	0.25	-0.14
Historical Beta	1.00	0.99	0.99	0.99
Price To Book	1.9	2.0	1.9	2.0
Price to Earnings	16.1	15.8	16.1	15.8
Ret on Equity (%)	11.8	12.7	11.8	12.7
Dividend Yield (%)	2.7	2.8	2.7	2.8
ESG Score	5.3	6.3	5.4	6.2
ESG Trend Pos (%)	17.8	19.2	19.8	20.1
Turnover (% p.a.)	2.2	7.9	8.3	10.2
Days to Trade 95%	0.3	0.7	0.5	0.7

Table 4.2

Active Exposure (GEMLT Factors)	ESG Level	ESG Change	ESG Tilt (Lev + Chg)
Book to Price	-0.05	-0.01	-0.05
Earnings Yield	0.00	-0.01	0.00
Size	0.06	0.00	0.05
Mid Cap	-0.04	0.00	-0.04
Momentum	-0.01	0.00	-0.01
Long-Term Reversal	0.02	0.00	0.01
Beta	-0.05	-0.01	-0.04
Residual Volatility	-0.03	-0.01	-0.03
Leverage	0.01	0.01	0.00
Earnings Quality	0.00	-0.01	-0.01
Investment Quality	0.05	0.01	0.04
Profitability	0.03	0.00	0.03
Earnings Variability	-0.07	-0.01	-0.06
Dividend Yield	0.03	0.00	0.03
Growth	-0.01	0.01	-0.01
Liquidity	-0.02	0.01	-0.01

Figure 15.4. *Simulated benchmarks incorporating ESG (performance based on gross total return)*

Figure 15.4 shows that all three variants experienced low tracking errors and risk-adjusted performance (Sharpe ratio) in line with the MSCI World Index over our study period of June 2007–June 2016. This analysis suggests that it may be possible to construct diversified benchmarks that capture the broad opportunity set and incorporate ESG criteria through simple and transparent rules without impairing the ability of these benchmarks to reflect the performance of the underlying market.

Next, we examine how ESG criteria could be incorporated into passive portfolios that track traditional benchmarks. Passive management is a well-established portfolio implementation method, offering a transparent and efficient way to capture the returns associated with a market or asset class. Asset managers who offer standard passive investment solutions may wish to incorporate ESG into their portfolios but may wonder to what extend ESG may impair the ability of their passive strategies to capture market returns.

To address this question, we simulated optimized index tracking strategies that aim to maximize the portfolio's ESG rating subject to different active risk budgets[11]. Specifically, we tested four strategies with active risk budgets of 25, 50, 100 and 200 basis points. This analysis, presented in Figure 15.5, shows that optimized index tracking strategies have achieved substantial improvement in the ESG profile of the portfolio as well as superior risk-adjusted performance compared to the underlying benchmarks over our study period of June 2007–June 2016[12].

Table 5.1

Performance & Characteristics	MSCI World	ESG Tilt	TE 25	TE 50	TE 100	TE 200
Total Return (%)	3.1	3.0	3.2	3.2	3.3	4.1
Total Risk (%)	17.2	17.1	17.3	17.5	17.5	17.5
Return/Risk	0.18	0.18	0.18	0.19	0.19	0.23
Sharpe Ratio	0.13	0.13	0.14	0.14	0.14	0.19
Active Return (%)	0.0	-0.1	0.05	0.1	0.2	1.0
Tracking Error (%)	0.0	0.7	0.4	0.8	1.2	2.1
Information Ratio	NA	-0.14	0.13	0.16	0.14	0.47
Historical Beta	1.00	0.99	1.00	1.01	1.01	1.01
Price To Book	1.9	2.0	1.9	1.9	1.9	1.9
Price to Earnings	16.1	15.8	16.0	16.1	16.4	16.8
Ret on Equity (%)	11.8	12.7	11.9	11.8	11.6	11.3
Dividend Yield (%)	2.7	2.8	2.7	2.7	2.7	2.7
ESG Score	5.3	6.2	6.4	6.9	8.1	9.1
ESG Trend Pos (%)	17.8	20.1	16.6	16.8	15.6	11.4
Number of Stocks	1671	1472	767	447	311	222
Days to Trade 95%	0.3	0.7	1.4	2.9	4.9	18.4

Table 5.2

Active Exposure (GEMLT Factors)	ESG Tilt	TE 25	TE 50	TE 100	TE 200	200-Tilt
Book to Price	-0.05	-0.01	-0.01	-0.03	-0.04	0.01
Earnings Yield	0.00	0.00	0.00	-0.01	-0.05	-0.05
Size	0.05	0.01	0.00	-0.05	-0.18	-0.23
Mid Cap	-0.04	0.00	0.00	0.04	0.13	0.17
Momentum	-0.01	0.00	-0.01	-0.01	-0.03	-0.02
Long-Term Reversal	0.01	0.01	0.02	0.02	0.05	0.04
Beta	-0.04	0.01	0.00	-0.01	-0.08	-0.04
Residual Volatility	-0.03	-0.03	-0.07	-0.11	-0.19	-0.16
Leverage	0.00	-0.01	-0.01	-0.03	-0.01	-0.01
Earnings Quality	-0.01	0.01	0.02	0.00	0.00	0.01
Investment Quality	0.04	0.03	0.06	0.08	0.14	0.10
Profitability	0.03	0.00	0.01	0.02	0.04	0.01
Earnings Variability	-0.06	-0.03	-0.06	-0.10	-0.15	-0.09
Dividend Yield	0.03	0.01	0.02	0.01	-0.03	-0.06
Growth	-0.01	0.00	-0.01	-0.01	-0.01	0.00
Liquidity	-0.01	0.01	0.01	0.00	0.00	0.01

Figure 15.5. *Simulated passive strategies incorporating ESG (gross total return)*

11 The following constraints and parameters were used in the simulated index tracking strategies. The objective of the optimization was to maximize the ESG score of the index tracking portfolio, subject to *ex ante* active risks of 25, 50, 100 and 200 bps. All GEMLT style factors were left unconstrained. All GICS® sectors and countries were constrained to ± 5% w.r.t. the parent index. Max security weights were set at the minimum (parent weight +2%, parent weight*10). Min security weights were set at the maximum (parent weight –2%, 0). The simulated portfolios were rebalanced quarterly with an annual one way turnover budget of 20%.

12 These results are consistent with Nagy [NAG 16] who reports positive IR for optimized strategies based on current ratings and change in ratings, with the latter achieving higher IR.

The 2% active risk strategy achieved the highest IR and the largest improvement in ESG rating. Factor exposures show that maximizing ESG through active risk optimization tilted the portfolio toward companies with higher quality and lower volatility characteristics. These results suggest that there is scope for developing passive strategies that would capture the equity risk premium efficiently by tracking cap-weighted benchmarks while holding companies with superior ESG characteristics.

15.5. Integrating ESG into factor strategies

The correlation analysis presented in Figure 15.1 shows that ESG is linked to defensive factors such as low volatility and quality. In this section, we examine explicitly the impact of ESG integration on various factor-based strategies. We start with three typical defensive strategies targeting the low volatility, quality and yield factors and then examine three dynamic strategies targeting the value, size and momentum factors.

15.5.1. *Integrating ESG into minimum volatility*

Low-volatility strategies have become increasingly popular as many investors seek to lower the risk of their portfolio while maintaining high exposure to equities and their attractive long-term return characteristics. Minimum volatility strategies, in particular, offer a structured way to lower *ex ante* portfolio risk while controlling other exposure and investability parameters [ALI 16]. One important question for minimum volatility investors who wish to incorporate ESG considerations into their portfolios is how ESG may impact the risk reduction properties of low-volatility strategies.

Figure 15.6 presents five simulated minimum volatility strategies that are subject to the same factor exposure and investability constraints[13] and are rebalanced quarterly with a 40% annual one-way turnover budget. The five strategies incorporate a constraint on the ESG score of the portfolio, which gradually increases

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13 The following parameters were used in the simulated minimum volatility strategies. The objective of the optimization was to minimize *ex ante* risk. The beta and residual volatility factors were left unconstrained. All other GEMLT factors were constrained to within ±0.25 cross-sectional standard deviations w.r.t. the parent index. All GICS® sectors and countries were constrained within ±5% w.r.t. the parent index. Maximum asset weights were set at minimum (1.5%, parent weight*20). Minimum asset weights were set at 0.05% (for selected assets). Minimum volatility has a total risk minimization objective; therefore, we do not impose active risk constraints.

from 20% to 50% in terms of required improvement relative to the underlying benchmark index (MSCI World Index).

These historical simulations show that adding an ESG constraint increased realized volatility. However, the increase in volatility was only 50 basis points for a 30% improvement in ESG score. Volatility went up by 2.0% when we imposed a 50% improvement in the ESG characteristics of the portfolio. Even for a 50% improvement in ESG score, the minimum volatility that the portfolio experienced was still 4.3 percentage points lower than the MSCI World Index[14].

Table 6.1

Performance & Characteristics	MSCI World	Min Vol	ESG20	ESG30	ESG40	ESG50
Total Return (%)	3.1	6.7	6.9	6.7	6.4	6.1
Total Risk (%)	17.5	11.2	11.4	11.7	12.3	13.2
Return/Risk	0.18	0.60	0.60	0.57	0.52	0.47
Sharpe Ratio	0.14	0.55	0.56	0.53	0.47	0.42
Active Return (%)	0.0	3.6	3.8	3.7	3.3	3.1
Tracking Error (%)	0.0	9.3	8.8	8.2	7.3	6.0
Information Ratio	NA	0.39	0.43	0.45	0.45	0.51
Historical Beta	1.00	0.56	0.58	0.62	0.66	0.72
Price To Book	1.9	2.3	2.3	2.2	2.2	2.1
Price to Earnings	16.1	16.8	16.7	16.7	16.6	16.5
Ret on Equity (%)	11.8	13.7	13.8	13.2	13.3	12.7
Dividend Yield (%)	2.7	2.9	2.9	2.9	2.9	2.9
ESG Score	5.3	5.1	6.3	6.8	7.3	7.9
ESG Trend Pos (%)	17.9	11.5	11.5	11.5	12.2	13.7
Number of Stocks	1660	287	261	239	211	181
Days to Trade 95%	0.1	3.5	3.2	3.4	4.0	5.4

Table 6.2

Active Exposure (GEMLT Factors)	Min Vol	ESG20	ESG30	ESG40	ESG50	50-NC
Book to Price	-0.21	-0.20	-0.20	-0.19	-0.18	0.03
Earnings Yield	-0.11	-0.10	-0.10	-0.10	-0.10	0.01
Size	-0.25	-0.24	-0.23	-0.21	-0.17	0.08
Mid Cap	0.19	0.18	0.17	0.16	0.13	-0.06
Momentum	0.09	0.09	0.08	0.07	0.05	-0.04
Long-Term Reversal	-0.02	-0.01	-0.02	-0.01	0.01	0.03
Beta	-1.02	-0.97	-0.92	-0.85	-0.74	0.28
Residual Volatility	-0.19	-0.21	-0.21	-0.21	-0.19	0.00
Leverage	0.04	0.04	0.03	0.03	0.02	-0.02
Earnings Quality	0.02	0.04	0.04	0.05	0.05	0.03
Investment Quality	0.14	0.15	0.16	0.16	0.16	0.02
Profitability	0.20	0.20	0.20	0.19	0.20	0.00
Earnings Variability	-0.26	-0.26	-0.26	-0.25	-0.25	0.01
Dividend Yield	0.19	0.19	0.19	0.18	0.16	-0.03
Growth	-0.16	-0.15	-0.14	-0.13	-0.12	0.04
Liquidity	-0.22	-0.21	-0.20	-0.18	-0.15	0.07

Chart 6.1

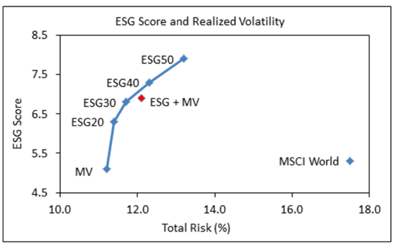

Chart 6.2

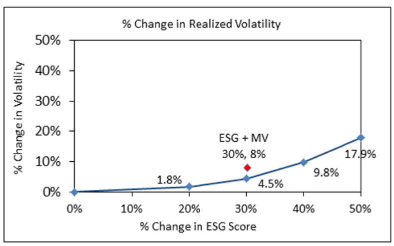

Figure 15.6. *Impact of ESG on minimum volatility strategies*

An alternative to this integrated approach would be a two-step process (denoted in Figure 15.6 as ESG + MV) where we first exclude securities with ESG ratings below 5 and then minimize volatility on the remaining universe. Charts 6.1 and 6.2 in Figure 15.6 show that the integrated approach dominates the two-step process as the latter lies below the ESG-volatility "efficient frontier". The two-step process led to an 8% increase in

14 From a statistical significance perspective, only the realized volatility of the ESG50 strategy is statistically significantly higher than the realized volatility of the simulated unconstrained minimum volatility strategy at a 90% confidence level.

volatility for 30% ESG enhancement while the integrated approach only led to a 4.5% rise in volatility for the same 30% increase in ESG score.

Overall, enhancing the ESG profile did not alter the exposures of the minimum volatility strategy and only led to a minor increase in realized volatility that was not statistically significant. It may therefore be possible to improve the ESG ratings of minimum volatility strategies without a material impact on the risk reduction properties and overall characteristics of the strategy.

15.5.2. *Integrating ESG into quality strategies*

Quality strategies typically focus on companies with high profitability, stable earnings, low accruals, conservative investments and low financial leverage. Historical long-term outperformance of quality stocks has been reported in a number of empirical studies (for example [NOV 13]). Also, many active investment management processes incorporate quality as a security selection criterion.

Examining ESG in the context of a factor model, our results show that companies with high quality characteristics tend to have above average ESG ratings (see Figure 15.1). In earlier research, Lee *et al*. [LEE 15] examined rules-based portfolio construction strategies combining financial quality and corporate governance. They reported that combining these two attributes resulted in superior risk-adjusted performance. In this section, we look at the impact of integrating ESG into a quality strategy through optimization while maintaining all other portfolio parameters constant.

Figure 15.7 shows simulations of a systematic quality strategy with a gradually improving ESG profile. This strategy and all other strategies examined in the remainder of this chapter are rebalanced quarterly with a 40% annual one-way turnover budget. The strategy uses optimization to maximize quality factor exposure subject to 3% *ex ante* active risk relative to the MSCI World Index[15]. We choose 3% active risk as this is representative of institutional active strategies. Figure 15.7 shows that improving the ESG profile of the strategy left the information ratio

15 The target factor for the simulated quality strategy was an equally weighted combination of the profitability, earnings quality and investment quality factors from GEMLT. In addition, the earnings variability and leverage factors were left unconstrained as they are typically associated with quality. All other GEMLT style factors were constrained to within ± 0.25 cross-sectional standard deviations w.r.t. the parent index. All GICS® sectors and countries were constrained within ±5% w.r.t. the parent index. Max security weights were set at minimum (parent weight +2%, parent weight*10). Minimum security weights were set at maximum (parent weight –2%, 0).

constant and only had a modest impact on the strategy's ability to find stocks with quality characteristics. In addition to the integrated approach, we also examined a two-step process that eliminates stocks with ESG score below 5 and then maximizes quality on the remaining universe (ESG + QTY). Similar to minimum volatility, the two-step approach was dominated by the integrated approach as it resulted in lower ESG scores for the same level of exposure to quality.

Table 7.1

Performance & Characteristics	MSCI World	Quality	ESG20	ESG30	ESG40	ESG50
Total Return (%)	3.1	6.4	6.6	6.6	6.0	5.8
Total Risk (%)	17.5	15.6	15.5	15.6	15.9	16.2
Return/Risk	0.18	0.41	0.43	0.42	0.38	0.36
Sharpe Ratio	0.14	0.38	0.39	0.39	0.34	0.33
Active Return (%)	0.0	3.3	3.5	3.5	2.9	2.8
Tracking Error (%)	0.0	3.1	3.1	3.1	2.8	2.6
Information Ratio	NA	1.09	1.13	1.15	1.05	1.05
Historical Beta	1.00	0.88	0.88	0.88	0.90	0.92
Price To Book	1.9	2.4	2.3	2.3	2.3	2.2
Price to Earnings	16.1	16.3	16.3	16.5	16.7	16.7
Ret on Equity (%)	11.8	14.7	14.1	13.9	13.8	13.2
Dividend Yield (%)	2.7	2.7	2.8	2.8	2.8	2.8
ESG Score	5.3	5.6	6.4	6.9	7.4	7.9
ESG Trend Pos (%)	17.9	20.8	16.5	17.4	18.6	19.8
Number of Stocks	1660	368	338	316	277	238
Days to Trade 95%	0.1	3.6	3.7	4.0	3.6	4.1

Table 7.2

Active Exposure (GEMLT Factors)	Quality	ESG20	ESG30	ESG40	ESG50	50-NC
Book to Price	-0.23	-0.23	-0.23	-0.22	-0.21	0.02
Earnings Yield	-0.01	-0.01	-0.02	-0.02	-0.03	-0.02
Size	-0.17	-0.13	-0.11	-0.08	-0.03	0.14
Mid Cap	0.12	0.09	0.08	0.06	0.02	-0.10
Momentum	0.07	0.06	0.06	0.05	0.05	-0.02
Long-Term Reversal	-0.03	-0.02	-0.01	-0.01	0.00	0.03
Beta	-0.24	-0.24	-0.24	-0.24	-0.23	0.01
Residual Volatility	-0.06	-0.08	-0.09	-0.09	-0.09	-0.03
Leverage	0.06	0.01	0.00	-0.01	-0.02	-0.08
Earnings Quality	0.49	0.46	0.43	0.38	0.29	-0.20
Investm Quality	0.53	0.51	0.49	0.44	0.38	-0.15
Profitability	0.80	0.76	0.70	0.62	0.50	-0.30
Earnings Variab	-0.11	-0.14	-0.16	-0.17	-0.20	-0.09
Dividend Yield	0.08	0.08	0.08	0.07	0.06	-0.02
Growth	-0.09	-0.10	-0.09	-0.09	-0.08	0.01
Liquidity	-0.03	-0.03	-0.03	-0.04	-0.04	-0.01

Chart 7.1

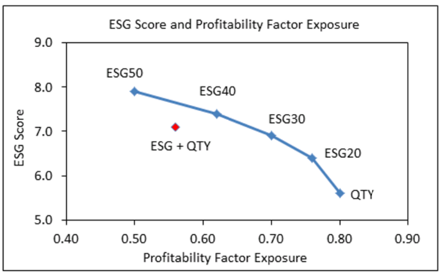

Chart 7.2

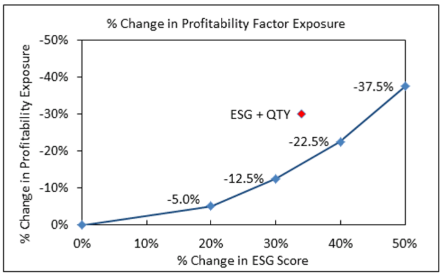

Figure 15.7. *Impact of ESG on quality strategies*

15.5.3. *Integrating ESG into yield strategies*

Income investing has a long tradition in equity portfolio management. Quantitative easing policies and aggressive interest rate cuts implemented by most major central banks since the global financial crisis have led to unprecedented levels of low or even negative interest rates across large swathes of the fixed income opportunity set, leading many investors to seek income through high dividend yield (HDY) equities. How are these strategies affected when ESG considerations are incorporated into the portfolio construction process? Can yield investors harvest equity income in a sustainable manner? Are HDY strategies with superior ESG profiles able to meet their primary objective of delivering a high level of yield while maintaining similar risk-adjusted total returns?

In Figure 15.8, we review the impact of incorporating ESG into HDY strategies. To ensure results are comparable across strategies, we use the same optimized portfolio construction framework that we used for quality[16]. We set a 3% active risk budget and maximize portfolio exposure to the dividend yield factor. Without any constraint on ESG, this simulated HDY strategy achieves an information ratio of 0.59 and an average dividend yield of 4.8% over our period of analysis. When we enhance the ESG profile of the HDY portfolio by 30%, dividend yields decline to 4.4% while the IR increases to 0.65. When we implement a more aggressive 50% increase in ESG, dividend yield drops to 3.8% but remains well above the market level of 2.7% while the IR of the strategy actually improves from 0.59 to 0.67. ESG integration improved performance and only had a modest impact on dividend yield.

Table 8.1

Performance & Characteristics	MSCI World	HDY	ESG20	ESG30	ESG40	ESG50
Total Return (%)	3.1	5.4	5.2	5.4	5.4	5.0
Total Risk (%)	17.5	15.9	15.9	15.9	16.0	16.3
Return/Risk	0.18	0.34	0.33	0.34	0.34	0.31
Sharpe Ratio	0.14	0.30	0.29	0.31	0.30	0.27
Active Return (%)	0.0	2.3	2.1	2.4	2.3	1.9
Tracking Error (%)	0.0	3.9	3.8	3.7	3.4	2.9
Information Ratio	NA	0.59	0.56	0.65	0.68	0.67
Historical Beta	1.00	0.89	0.89	0.89	0.90	0.92
Price To Book	1.9	1.8	1.8	1.8	1.8	1.8
Price to Earnings	16.1	14.2	14.5	14.6	14.8	15.0
Ret on Equity (%)	11.8	12.7	12.4	12.3	12.2	12.0
Dividend Yield (%)	2.7	4.8	4.6	4.4	4.2	3.8
ESG Score	5.3	4.8	6.3	6.9	7.4	7.9
ESG Trend Pos (%)	17.9	18.7	19.0	17.8	17.9	14.6
Number of Stocks	1660	303	449	400	394	334
Days to Trade 95%	0.1	3.4	3.7	4.0	4.4	3.9

Table 8.2

Active Exposure (GEMLT Factors)	HDY	ESG20	ESG30	ESG40	ESG50	50-NC
Book to Price	0.06	0.04	0.02	0.01	0.00	-0.06
Earnings Yield	0.15	0.13	0.13	0.12	0.11	-0.04
Size	-0.10	-0.02	-0.01	0.03	0.06	0.16
Mid Cap	0.06	0.01	0.00	-0.03	-0.05	-0.11
Momentum	-0.06	-0.06	-0.05	-0.05	-0.03	0.03
Long-Term Reversal	0.05	0.07	0.07	0.07	0.05	0.00
Beta	-0.23	-0.24	-0.24	-0.24	-0.23	0.00
Residual Volatility	-0.14	-0.14	-0.15	-0.16	-0.14	0.00
Leverage	0.18	0.17	0.14	0.09	0.07	-0.11
Earnings Quality	0.12	0.12	0.11	0.10	0.09	-0.03
Investment Quality	0.10	0.11	0.13	0.16	0.19	0.09
Profitability	-0.05	-0.04	-0.03	-0.01	-0.01	0.04
Earnings Variability	-0.07	-0.11	-0.14	-0.16	-0.19	-0.12
Dividend Yield	1.13	1.03	0.94	0.82	0.63	-0.50
Growth	-0.26	-0.26	-0.25	-0.24	-0.21	0.05
Liquidity	-0.07	-0.11	-0.11	-0.12	-0.13	-0.06

Chart 8.1

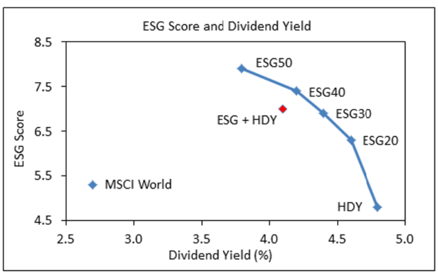

Chart 8.2

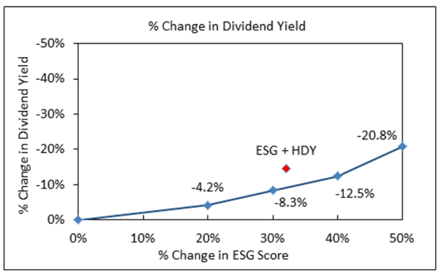

Figure 15.8. *Impact of ESG on high dividend yield strategies*

16 The target factor for the simulated high yield strategies was the dividend yield factor in the GEMLT model. All other optimization constraints and parameters were exactly the same as for the simulated quality strategy.

15.5.4. *Integrating ESG into value strategies*

Value investing is well established across the active portfolio management industry. Many research studies show that value strategies have a strong long-term performance record (for example, see [CHE 98]) but value has recently suffered a period of underperformance. Has ESG improved the historical performance of value strategies? To what extend does adding ESG raise valuations and may therefore prevent value managers from meeting their stated investment objective of holding companies that have attractive valuations?

Figure 15.9 shows simulations of a systematic value strategy with a gradually improving ESG profile. The strategy uses optimization to maximize exposure to the value factor subject to 3% active risk[17]. Improving the ESG profile of this value strategy led to a higher information ratio historically and only had a modest impact on the strategy's ability to select stocks with attractive valuations. For example, the average price-earnings (PE) ratio of the strategy only increased from 10.6 to 11.3 for 30% ESG improvement. Even for 50% ESG enhancement, the PE ratio only rose by 20% to 12.8 and remained well below the market multiple of 16.1. Factor analysis reveals that enhancing the ESG rating of the strategy led to lower exposure to value factors while size exposure increased and earnings variability exposure fell. Introducing ESG into a value strategy tilted the portfolio toward larger companies with more stable earnings.

15.5.5. *Integrating ESG into momentum strategies*

We used the same systematic portfolio construction framework to investigate the impact of ESG on momentum strategies[18]. As Figure 15.10 shows, we observe a minor drop in risk-adjusted performance (information ratio) from 0.95 to 0.82 and a reduction in target factor exposure of 13.3% for a 30% improvement in the ESG rating of an optimized 3% active risk momentum strategy. Factor exposure analysis reveals that ESG integration reduced the negative size bias of the unconstrained momentum strategy and its exposure to the leverage and earnings variability factors.

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17 The target factor for the value strategy was a combination of 80% earnings yield factor exposure and 20% book-to-price factor exposure, using the two factors in GEMLT; 80% weight was assigned to earnings yield as it contains four value descriptors and 20% weight was assigned to the book-to-price factor as it contains only one descriptor. All other optimization parameters were exactly the same as for the simulated quality strategy.

18 The target factor for the simulated momentum strategies was the momentum factor in the GEMLT model. All other optimization constraints and parameters were exactly the same as for the simulated quality strategy.

Table 9.1

Performance & Characteristics	MSCI World	Value	ESG20	ESG30	ESG40	ESG50
Total Return (%)	3.1	4.3	4.4	4.5	4.7	4.8
Total Risk (%)	17.5	16.0	16.0	16.2	16.4	16.5
Return/Risk	0.18	0.27	0.28	0.28	0.29	0.29
Sharpe Ratio	0.14	0.23	0.24	0.24	0.26	0.26
Active Return (%)	0.0	1.2	1.4	1.4	1.6	1.7
Tracking Error (%)	0.0	3.1	2.9	2.7	2.6	2.4
Information Ratio	NA	0.40	0.47	0.53	0.64	0.71
Historical Beta	1.00	0.90	0.90	0.92	0.93	0.94
Price To Book	1.9	1.5	1.5	1.6	1.6	1.7
Price to Earnings	16.1	10.6	10.9	11.3	11.9	12.8
Ret on Equity (%)	11.8	14.2	13.8	14.2	13.4	13.3
Dividend Yield (%)	2.7	3.0	3.0	3.0	3.0	3.0
ESG Score	5.3	4.9	6.3	6.8	7.4	7.9
ESG Trend Pos (%)	17.9	19.2	16.9	14.1	14.5	15.8
Number of Stocks	1660	368	328	298	265	399
Days to Trade 95%	0.1	3.6	3.9	4.2	4.0	4.0

Table 9.2

Active Exposure (GEMLT Factors)	Value	ESG20	ESG30	ESG40	ESG50	50-NC
Book to Price	0.42	0.34	0.28	0.22	0.12	-0.30
Earnings Yield	0.65	0.60	0.55	0.48	0.37	-0.28
Size	-0.14	-0.09	-0.05	-0.01	0.02	0.16
Mid Cap	0.10	0.06	0.03	0.00	-0.02	-0.12
Momentum	-0.03	-0.03	-0.03	-0.03	-0.03	0.00
Long-Term Reversal	0.01	0.01	0.02	0.03	0.03	0.02
Beta	-0.24	-0.24	-0.24	-0.23	-0.23	0.01
Residual Volatility	-0.12	-0.13	-0.13	-0.14	-0.14	-0.02
Leverage	-0.03	-0.05	-0.05	-0.05	-0.04	-0.01
Earnings Quality	0.07	0.09	0.08	0.07	0.04	-0.03
Investment Quality	0.11	0.13	0.15	0.16	0.17	0.06
Profitability	0.02	0.04	0.05	0.05	0.05	0.03
Earnings Variability	0.03	-0.01	-0.03	-0.08	-0.14	-0.17
Dividend Yield	0.24	0.23	0.23	0.22	0.20	-0.04
Growth	-0.22	-0.21	-0.20	-0.18	-0.15	0.07
Liquidity	-0.03	-0.03	-0.04	-0.05	-0.07	-0.04

Chart 9.1

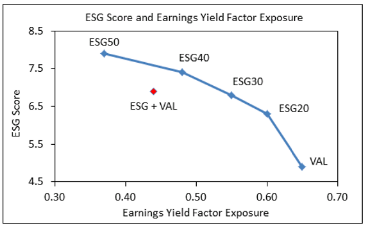


Chart 9.2

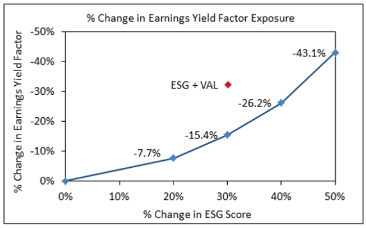


Figure 15.9. *Impact of ESG on value strategies*

Table 10.1

Performance & Characteristics	MSCI World	MOM	ESG20	ESG30	ESG40	ESG50
Total Return (%)	3.1	6.4	5.9	5.7	5.3	5.3
Total Risk (%)	17.5	15.6	15.6	15.8	16.0	16.2
Return/Risk	0.18	0.41	0.38	0.36	0.33	0.33
Sharpe Ratio	0.14	0.38	0.34	0.32	0.30	0.30
Active Return (%)	0.0	3.3	2.8	2.6	2.2	2.3
Tracking Error (%)	0.0	3.5	3.4	3.2	2.9	2.7
Information Ratio	NA	0.95	0.85	0.82	0.76	0.84
Historical Beta	1.00	0.88	0.88	0.89	0.90	0.92
Price To Book	1.9	2.3	2.3	2.3	2.3	2.2
Price to Earnings	16.1	16.1	16.2	16.3	16.3	16.6
Ret on Equity (%)	11.8	14.3	14.2	14.1	14.1	13.3
Dividend Yield (%)	2.7	2.4	2.4	2.4	2.5	2.5
ESG Score	5.3	5.2	6.3	6.8	7.3	7.9
ESG Trend Pos (%)	17.9	19.2	15.4	15.4	15.4	14.6
Number of Stocks	1660	510	429	374	314	445
Days to Trade 95%	0.1	2.9	2.8	2.8	2.9	2.9

Table 10.2

Active Exposure (GEMLT Factors)	MOM	ESG20	ESG30	ESG40	ESG50	50-NC
Book to Price	-0.19	-0.20	-0.20	-0.20	-0.20	-0.01
Earnings Yield	-0.07	-0.07	-0.08	-0.08	-0.08	-0.01
Size	-0.17	-0.13	-0.10	-0.07	-0.02	0.15
Mid Cap	0.14	0.10	0.08	0.05	0.02	-0.12
Momentum	0.45	0.42	0.39	0.34	0.27	-0.18
Long-Term Reversal	-0.22	-0.21	-0.19	-0.16	-0.11	0.11
Beta	-0.22	-0.22	-0.23	-0.23	-0.23	-0.01
Residual Volatility	0.03	0.02	0.01	-0.01	-0.03	-0.06
Leverage	0.01	-0.02	-0.04	-0.05	-0.06	-0.07
Earnings Quality	-0.02	0.01	0.01	0.01	-0.01	0.01
Investment Quality	0.08	0.09	0.10	0.11	0.13	0.05
Profitability	0.18	0.18	0.19	0.19	0.19	0.01
Earnings Variability	0.00	-0.05	-0.08	-0.12	-0.17	-0.17
Dividend Yield	-0.09	-0.09	-0.10	-0.09	-0.08	0.01
Growth	0.09	0.08	0.08	0.07	0.05	-0.04
Liquidity	0.02	0.02	0.01	0.00	-0.03	-0.05

Chart 10.1

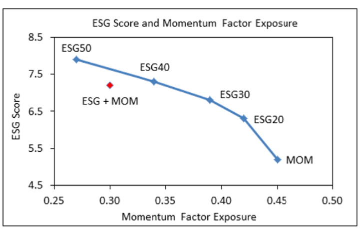


Chart 10.2

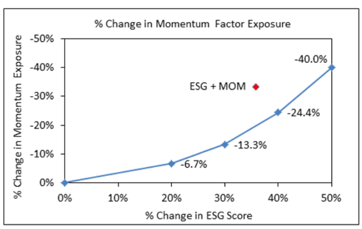


Figure 15.10. *Impact of ESG on momentum strategies*

15.5.6. *Integrating ESG into low-size strategies*

We complete the empirical portfolio construction analysis by investigating the impact of ESG on low-size strategies[19]. Figure 15.11 shows that for a 30% improvement in the ESG rating of an optimized 3% active risk low-size strategy, we observe that IR dropped from 0.94 to 0.65 while size factor exposure diminished by 22%.

Table 11.1

Performance & Characteristics	MSCI World	Size	ESG20	ESG30	ESG40	ESG50
Total Return (%)	3.1	6.3	5.3	5.2	5.1	5.0
Total Risk (%)	17.5	16.1	16.4	16.5	16.5	16.7
Return/Risk	0.18	0.39	0.32	0.32	0.31	0.30
Sharpe Ratio	0.14	0.36	0.29	0.28	0.28	0.27
Active Return (%)	0.0	3.2	2.2	2.1	2.0	2.0
Tracking Error (%)	0.0	3.4	3.3	3.2	3.1	3.0
Information Ratio	NA	0.94	0.67	0.65	0.65	0.66
Historical Beta	1.00	0.90	0.92	0.93	0.93	0.94
Price To Book	1.9	1.9	1.9	1.9	2.0	2.0
Price to Earnings	16.1	18.4	18.3	18.3	18.2	17.8
Ret on Equity (%)	11.8	10.3	10.4	10.4	11.0	11.2
Dividend Yield (%)	2.7	2.4	2.4	2.4	2.5	2.5
ESG Score	5.3	4.8	6.3	6.9	7.4	7.9
ESG Trend Pos (%)	17.9	12.5	13.2	13.0	14.0	15.0
Number of Stocks	1660	1001	846	773	637	520
Days to Trade 95%	0.1	3.6	4.0	4.2	4.4	4.6

Table 11.2

Active Exposure (GEMLT Factors)	Size	ESG20	ESG30	ESG40	ESG50	50-NC
Book to Price	0.03	-0.02	-0.05	-0.08	-0.11	-0.14
Earnings Yield	-0.19	-0.19	-0.19	-0.18	-0.15	0.04
Size	-1.12	-0.97	-0.87	-0.73	-0.54	0.58
Mid Cap	0.79	0.69	0.62	0.52	0.38	-0.41
Momentum	0.03	0.03	0.04	0.04	0.04	0.01
Long-Term Reversal	0.00	0.01	0.01	0.01	0.01	0.01
Beta	-0.23	-0.23	-0.23	-0.23	-0.23	0.00
Residual Volatility	-0.25	-0.25	-0.25	-0.24	-0.23	0.02
Leverage	0.06	0.04	0.03	0.03	0.03	-0.03
Earnings Quality	0.00	0.02	0.03	0.04	0.04	0.04
Investment Quality	0.00	0.03	0.06	0.08	0.11	0.11
Profitability	0.07	0.10	0.12	0.13	0.15	0.08
Earnings Variability	0.00	-0.05	-0.07	-0.11	-0.14	-0.14
Dividend Yield	-0.17	-0.15	-0.14	-0.11	-0.09	0.08
Growth	-0.03	-0.03	-0.02	-0.02	-0.02	0.01
Liquidity	0.18	0.18	0.17	0.14	0.10	-0.08

Chart 11.1

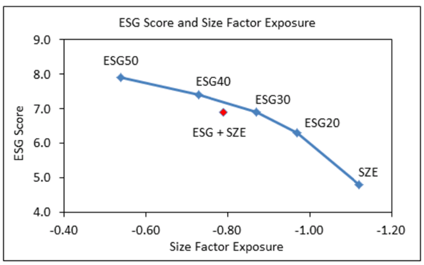


Chart 11.2

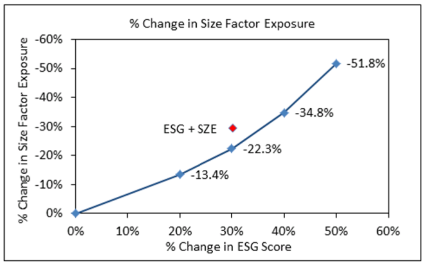


Figure 15.11. *Impact of ESG on simulated size strategies, analysis over period December 2007–June 2016*

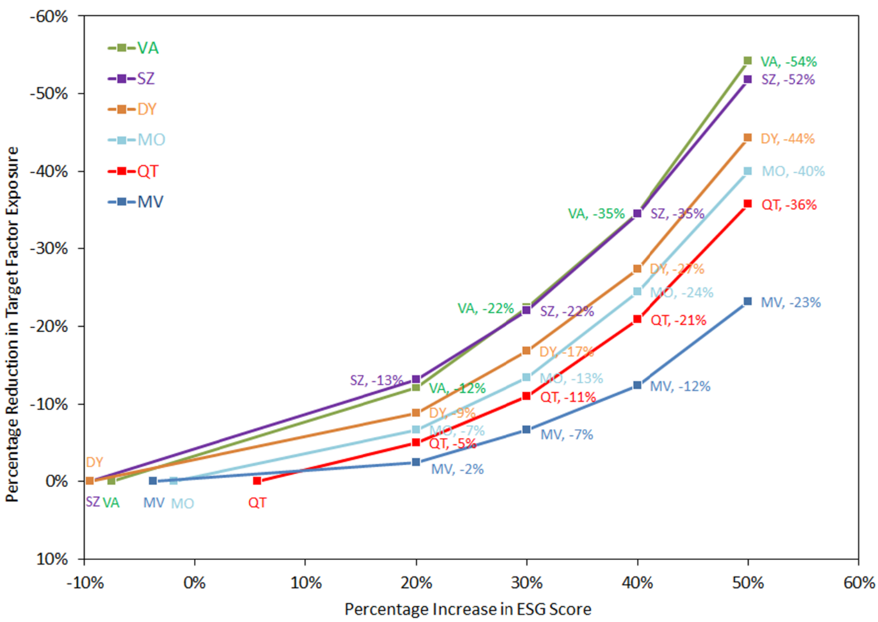
15.6. Summary of results and implications for portfolio construction

We examined the impact of incorporating ESG criteria on passive and active investment strategies. We used familiar factors as proxies for active strategies. Our results show that ESG has generally had a positive impact on historical risk-adjusted

19 The target factor for the simulated low-size strategies was the size factor in the GEMLT model. All other optimization constraints and parameters were exactly the same as for the simulated quality strategy.

performances of the strategies we evaluated. Incorporating ESG tilted the original strategies toward stocks with higher market capitalization, better earnings quality, improved earnings stability, lower leverage and lower residual volatility. The improvement in historical performance was attributed to these factor tilts as well as to specific sources of return.

Historical performance is no guarantee of future results. That is why we examined closely the impact of ESG on each strategy's ability to pursue its stated investment objective. Passive investors need to be able to capture market returns efficiently after they add ESG to their portfolios. Factor strategies need to be able to maintain high exposure to their target factors and active managers must retain enough flexibility to find alpha opportunities through their active security selection process.



VA, value; SZ, size; DY, dividend yield; MO, momentum; QT, quality; MV, minimum volatility

Figure 15.12. *Impact of ESG integration factor strategies. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

To quantify the potential impact of ESG integration on the *ex ante* information ratio of different strategies, we focus on *percentage reduction in target factor* *exposure*. As target factor exposures are effectively expected return proxies for factor strategies, percentage reduction in active target factor exposure is the right measure to quantify the impact of ESG on the *ex ante* information ratios of these strategies. In other words, for factor investors, x% reduction in target factor exposure due to adding ESG translates directly into x% drop in *ex ante* information ratios, everything else being equal.

Figure 15.14 shows the trade-off between increases in ESG score and reductions in target factor exposure[20] for the strategies we evaluated. This figure shows that material improvement in the ESG profile of these strategies of the order of 30% was achieved with relatively modest impact on target factor exposure, ranging between 7 and 22%. When we seek more substantial ESG improvement, the reduction in target factor exposure becomes higher. For 50% ESG enhancement, the impact on target factor exposure ranged from 23 to 54%.

This figure also shows clearly that not all strategies were affected to the same extent. Incorporating ESG had remarkably low impact on simulated minimum volatility strategies. Target factor exposure only decreased by 7% for a 30% ESG uplift. Simulated quality strategies were also impacted relatively modestly, suffering an 11% reduction in target factor exposure for a 30% improvement in ESG rating. On the other hand, value, size, momentum and yield strategies experienced more material target factor exposure reductions ranging between 13% and 22% for 30% ESG enhancement.

15.7. Conclusion

Our results may provide guidance to passive and active managers that wish to incorporate ESG criteria into their strategies. They show that ESG has generally improved the historical information ratio of many typical passive and factor-based investment strategies. They also show that the impact of ESG integration on the *ex ante* information ratio of these strategies is relatively moderate and varies according to the primary investment objective and target factors of the underlying strategy.

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20 Target factors for each of the six strategies were defined based on GEMLT factors as follows. For minimum volatility, we took the average of beta and residual volatility. For the quality strategy, we took the average of earnings quality, investment quality and profitability. For the value strategy, we used the average of the earnings yield and book-to-price factors. For the low size strategy, we took the average of size and midcap, with the latter sign inverted for obvious reasons. Finally, for the high dividend yield and for the momentum strategies we used the dividend yield factor and the momentum factor, respectively.

15.8. Appendices

15.8.1. *Appendix 1: Does an ESG constraint improve the overall sustainability profile?*

Inventors who integrate ESG considerations into their strategies are typically motivated by specific objectives rather than a general improvement in the weighted average ESG score of the portfolio. These objectives may include long-term risk considerations, for example avoiding investments in companies that are involved in certain types of activities, have high carbon exposure or suffer from severe controversies associated with their ESG related policies and practices. Other investors may place more emphasis on a particular pillar, for example the governance pillar, and may wish to quantify how their strategy has superior characteristics relative to the broad investment universe.

How did a portfolio constraint at the ESG score level impact these multiple dimensions of sustainable investing? The analysis in Figure 15.13 shows more detailed information about several ESG-related metrics for the simulated minimum volatility and quality strategies[21]. This analysis looks beyond the portfolio level ESG score and drills down into specific themes associated with sustainable investing.

ESG Metrics	MSCI World	Min Vol	ESG20	ESG30	ESG40	ESG50
Key Integration Metrics						
ESG Score	5.3	5.1	6.3	6.8	7.3	7.9
ESG Leaders (AAA-AA) (%)	20.8	18.1	33.5	42.5	52.7	64.9
ESG Laggards (B-CCC) (%)	17.0	14.8	4.3	2.3	1.1	0.0
ESG Pillars						
Environmental Score	5.5	5.4	6.0	6.3	6.5	6.7
Social Score	4.3	4.1	4.6	4.9	5.2	5.5
Governance Score	5.0	4.9	5.2	5.3	5.5	5.6
Key Governance Metrics						
Lack of Indep. Board Majority (%)	13.1	15.4	15.0	15.6	16.7	17.3
Deviation from 1 Share1 Vote (%)	21.3	22.9	21.1	19.5	17.3	15.0
No Female Directors (%)	6.6	9.5	8.7	8.5	8.6	8.2
Values						
Global Compliance Watch List (%)	13.9	12.5	8.8	6.5	4.4	3.6
Red Flag Controversies (%)	2.8	1.4	1.0	0.9	0.5	0.0
Orange Flag Controversies (%)	27.8	22.7	19.2	17.4	15.9	14.6

ESG Metrics	MSCI World	Qual	ESG20	ESG30	ESG40	ESG50
Key Integration Metrics						
ESG Score	5.3	5.6	6.4	6.9	7.4	7.9
ESG Leaders (AAA-AA) (%)	20.8	25.8	36.6	46.6	57.3	68.5
ESG Laggards (B-CCC) (%)	17.0	11.1	4.6	1.6	0.8	0.2
ESG Pillars						
Environmental Score	5.5	5.9	6.3	6.5	6.8	7.0
Social Score	4.3	4.3	4.7	5.0	5.2	5.4
Governance Score	5.0	5.0	5.2	5.3	5.5	5.7
Key Governance Metrics						
Lack of Indep. Board Majority (%)	13.1	18.6	17.6	17.8	16.9	16.1
Deviation from 1 Share1 Vote (%)	21.3	19.9	17.5	16.0	15.0	15.8
No Female Directors (%)	6.6	7.4	7.6	7.7	6.9	6.4
Values						
Global Compliance Watch List (%)	13.9	12.1	6.5	6.3	4.9	5.8
Red Flag Controversies (%)	2.8	3.9	1.9	1.0	0.0	0.0
Orange Flag Controversies (%)	27.8	21.5	20.2	20.5	17.5	17.3

ESG20, ESG30, ESG40 and ESG50 correspond to strategies incorporating 20%, 30%, 40% and 50% ESG enhancements, respectively. ESG Leaders are stocks rated AAA or AA. ESG Laggards are stocks rated B or CCC. Also please see references in footnote 5.

Figure 15.13. *ESG constraint impact on key ESG metrics. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

21 We show detailed ESG metrics for these two strategies only as they are the most likely candidates for ESG integration due to their defensive nature. We conducted the same analysis for all simulated strategies with broadly similar conclusions. These additional results are available upon request.

The results reported in Figure 15.13 show that portfolio level ESG score improvement was achieved by both overweighting leaders and underweighting laggards. In addition, even though our simulations only constrained the ESG score, we observe consistent and material improvement across all three individual pillar scores. The same consistently improving picture emerges when we examine the portfolio allocation to companies on the watch list and those that are subject to ESG controversies[22].

Enhancing the ESG score of the simulated strategies also led to a consistent and significant reduction in portfolio allocation to companies that deviate from the one-share one-vote principle. We generally observe reduced allocation to companies that lack any female directors relative to the unconstrained variants but not relative to the underlying parent index. Finally, we do not see any clear trend in terms of portfolio allocations to companies that lack an independent board majority. Overall, top level ESG constraints improved substantively most of the ESG dimensions we evaluated.

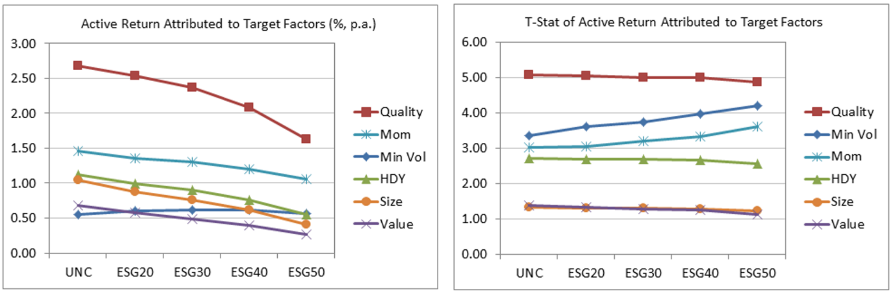
15.8.2. *Appendix 2: Are factors significant sources of performance after integrating ESG?*

In this appendix, we use factor attribution to decompose the active return of each simulated strategy into systematic and specific sources. In addition, we assess whether the return attributed to these sources was statistically significant. If returns attributed to the target factors remained significant throughout the range of ESG score improvement we investigated, this would provide flexibility to asset owners and asset managers to express their ESG objectives without fear that their investment strategies would be compromised. On the other hand, if target factor returns became insignificant above a certain threshold of ESG exposure, this threshold may serve as a guideline for ensuring the relevant investment strategy retains sufficient flexibility to pursue its primary investment objective.

Factor attribution analysis, presented in Figure 15.14, confirms that ESG integration into defensive strategies did not impair the ability of these strategies to generate significant active returns from their target factors. Active returns attributed to residual volatility, profitability, earnings quality, investment quality and dividend yield remained relatively high and statistically significant through the range of examined ESG enhancements. Investors pursuing these defensive strategies could have improved the ESG profile of their portfolios while still enjoying statistically

22 For more detailed information on the precise definition and method of calculation as well as the sources used to derive these measures, see [MSC 15].

significant positive target factor returns historically. The same holds true for momentum over the period of analysis. Value and low-size strategies also enjoyed positive active returns from their respective target factors but these returns were lower in magnitude and not statistically significant over our sample period.



ESG20, ESG30, ESG40 and ESG50 correspond to strategies incorporating 20%, 30%, 40% and 50% ESG enhancements respectively. UNC refers to the original strategies that did not include an ESG enhancement target, they were therefore unconstrained.

Figure 15.14. *Active return attribution to factors and statistical significance of attributed returns. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

15.8.3. *Appendix 3: How much ESG should you add to your portfolio?*

Figure 15.12 shows the percentage reduction in target factor exposure as a function of increase in ESG score. The slope of this line increases monotonically but at different rates for different strategies. For example, for minimum volatility it was 0.10 for 20% change in ESG and rose progressively to 0.46 for 50% change in ESG score, while for value it rose from 0.60 to 1.08 over the same interval. Is there a way to determine the "right" level of ESG enhancement? Can we link this level to factor exposures in typical active strategies? Does this level depend on the cross-sectional distribution of ESG scores?

Factor exposures of the order of 0.2 cross-sectional standard deviations (z-scores) are generally deemed significant in long only portfolios while empirical evidence suggests that active mutual funds which pursue dedicated strategies had approximately 0.5 standard deviation exposure to their target factors[23]. Figure 15.15

23 For example, Balint *et al*. [BAL 16] analyzed active US mutual funds based on their self-classifications and found average target factor exposure of 0.46 for value funds, 0.34 for momentum funds, 0.50 for volatility funds, 0.45 for quality funds, 0.36 for high dividend yield funds and 0.42 for growth funds, see Figure 15.4.

plots a time series of cross-sectional standard deviations for the ESG scores of MSCI World Index constituents. This standard deviation was around 2.6 during the earlier part of the sample and has recently dropped to about 2.3. In the same figure, we also plot the cross-sectional mean, median, 75th, 80th and 90th percentiles over time.

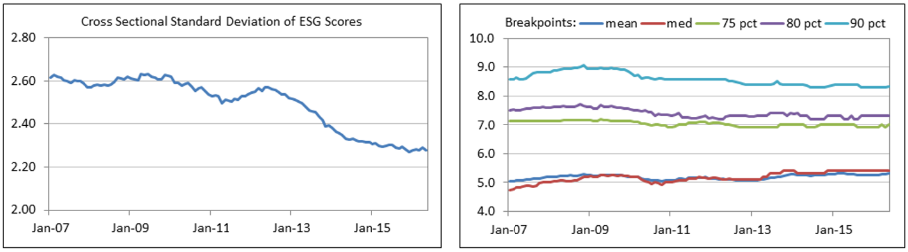


Figure 15.15. *Cross-sectional standard deviation and %-tile breakpoints of MSCI world ESG scores. For a color version of this figure, see www.iste.co.uk/jurczenko/investing.zip*

This analysis reveals that a 30% increase in ESG score relative to the market, which is equivalent to about 1.5 units, would roughly correspond to 0.57 cross-sectional standard deviations, a level similar to average target factor exposures of dedicated active mutual funds, reported in [BAL16]. An ESG increase of 40%, corresponding to about 2.0 units, would put the portfolio in the top quartile of cross-sectional stock level ESG scores. So this analysis reveals that 30% may be the right ESG level for an active investor, while 40% would locate the ESG rating of the portfolio in the top ESG quartile.

15.9. Bibliography

[ALI 16] ALIGHANBARI M., DOOLE S., SHANKAR D., "Designing low-volatility strategies", *Journal of Index Investing*, vol. 7, no. 3, pp. 21–33, 2016.

[BAL 16] BALINT I., MELAS D., Using Systematic Equity Strategies, MSCI Research Insight, available at www.msci.com, 2016.

[CHE 98] CHEN N., ZHANG F., "Risk and return of value stocks", *Journal of Business*, vol. 71, no. 4, pp. 501–535, 1998.

[FRI 15] FRIEDE G., BUSCH T., BASSEN A., "ESG and financial performance: aggregated evidence from more than 2000 empirical studies", *Journal of Sustainable Finance & Investment*, vol. 5, no. 4, pp. 210–233, 2015.

[HIT 15] HITCHENS R., MCCULLAGH S., PARKS C., Finding alpha in ESG, Credit Suisse, ESG-α series, 2015.

[JUS 13] JUSSA J., ALVAREZ M.-A., WANG S. *et al.*, SRI Integration Using Smart Beta, Deutsche Bank, Markets Research, 2013.

[LEE 15] LEE L.-E., DOOLE S., MARSHALL R. *et al.*, Raising Minimum Governance Standards – Selecting Quality Companies for the Long Term, MSCI Research Insight, available at www.msci.com, 2015.

[MEL 10] MELAS D., SURYANARAYANAN R., CAVAGLIA S., "Efficient replication of factor returns: theory and applications", *Journal of Portfolio Management*, vol. 36, no. 2, pp. 39–51, 2010.

[MEL 16] MELAS D., "Power to the people: the profound impact of factor investing on long term portfolio management", *Journal of Portfolio Management*, vol. 42, no. 2, pp. 6–8, 2016.

[MOR 15] MOROZOV A., MINOVITSKY S., WANG J. *et al.*, Barra global total market equity model for long-term investors, MSCI Empirical Notes, 2015.

[MSC 15] MSCI ESG RESEARCH, ESG Ratings Methodology, available at www.msci.com/eqb/methodology/meth_docs/Executive_Summary_MSCI_ESG_ Ratings_Methodology.pdf, 2015.

[NAG 13] NAGY Z., COGAN D., SINNREICH D., Optimizing Environmental, Social and Governance Factors in Portfolio Construction: Analysis of Three ESG-Tilted Strategies, MSCI Research Insight, available at www.msci.com, 2013.

[NAG 15] NAGY Z., KASSAM A., LEE L.-E., Can ESG Add Alpha?, MSCI Research Insight, available at www.msci.com, 2015.

[NOR 14] NORTHERN TRUST, "Doing good and doing well – how quality can enhance your ESG strategy", available at: www.northerntrust.com/doinggood, 2014.

[NOV 13] NOVY-MARX R., "The other side of value: the gross profitability premium", *Journal of Financial Economics*, vol. 108, no. 1, pp. 1–28, 2013.

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16

The Alpha and Beta of Equity Hedge UCITS Funds: Implications for Momentum Investing

Equity hedge Undertakings for Collective Investment in Transferable Securities (UCITS) funds pursue hedge fund-like active management strategies subject to high liquidity and transparency constraints, ensured by regulatory oversight. Understanding the performance of these alternative, UCITS funds is of utmost importance in fund selection and optimizing the portfolio allocation. When the fund-of-fund allocation is momentum based, we show that there is economic value in using factor models to disentangle the fund-specific residual performance (alpha) from the return component that can be explained by the fund's exposure to common style and asset-based factors (beta). We obtain this result through a detailed analysis of the equity hedge UCITS funds' net returns using both the peer return style-factor and asset-based risk factor models over the period 2010–2016. We find that the performance of a systematic monthly rebalanced momentum-based fund-of-fund allocation is improved when ranking funds using the residual performance after correcting for false discoveries, as compared to the traditional use of rolling averages of past returns.

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16.1. Introduction

Alternative UCITS is a pan-European regulatory framework that allows investment vehicles to be managed and sold throughout Europe. The unified fund structure provides retail investors access to a blend of sophisticated active management strategies subject to high liquidity and transparency constraints, which are ensured by regulatory oversight. The introduction of alternative UCITS funds under the UCITS III Product Directive fits in the so-called "retail alternatives phenomenon". The client base of alternative investments (apart from long-only allocations to equity and bonds) is increasingly composed of retail investors seeking absolute return investments characterized by low volatility, decorrelation with broad market movements [SEI 13, WIE 13, ANG 16] and exposure to alternative risk premia [HAM 16, see also Chapter 10 of this book]. Accordingly, the combined effect of strong efforts in investor-favorable regulation when investing in the hedge fund industry and a thematic shift in the mindset of the investor desiring hedge fund-like returns led to a substantial increase in terms of the number of alternative UCITS funds, assets under management (AuM) and market depth. In March 2017, the LuxHedge database reports a UCITS universe of €420 billion AuM across 1,380 funds operating under 16 distinct strategies.

Realistic portfolios invested in alternative UCITS funds are composed of a diversified set of at least 20 funds. Consistent with the *adaptive markets hypothesis* of [LO 04], we expect the set of outperforming funds to be time-varying. In this chapter, we therefore investigate the use of momentum strategies to detect the funds whose strategies are best adapted to the current market regime. Our approach builds on the hypothesis set in [BLI 11] that the performance of standard momentum strategies based on rolling averages of past returns can be improved by the use of residual return (alpha). We will use factor models in order to isolate the manager-specific component from common-factor performance using a peer return style factor or a portfolio invested in rule-based strategies capturing the asset-based risk factors. These results are also in line with the presence of a *hot hands* effect in fund performance [HEN 93] and the time variation in the alpha of hedge fund managers [AVR 11, CRI 14].

Our research contributes to the recent research agenda of understanding the sources of performance of alternative UCITS funds. At present, academic research is still scarce. Notable exceptions include the recent papers by [TUC 10, ZAN 12, GRE 13, TUC 13, DEW 13, DAR 14] and BUS 14, BUS 15]. Understanding the performance of alternative UCITS funds is of utmost importance in fund selection and optimizing the portfolio allocation. Consistent with the mainstream use of factor models to evaluate the performance of mutual funds and hedge funds, we make a distinction between investment style and asset-based return factors. On the part of complementing academic and practitioner literature, we extend the studied time interval and acknowledge the heterogeneity of the UCITS universe by applying factor models to disentangle the fund-specific (instead of strategy-specific) residual performance (alpha) from the joint return that can be explained by common style and asset-based factors (beta). The decomposition of the universe indicates heterogeneity across funds in terms of exposure to the factors and obtained residual performance. We find that only a small subset of funds shows evidence of statistically significant alpha surplus. Finally, we evaluate the informativeness of the residual return component by means of a portfolio sorting strategy. When the fund-of-fund allocation is momentum based, we show that there is economic value in using factor models. We find that the performance of a systematic monthly rebalanced momentum-based investment scheme is improved when ranking the funds using the fund's residual performance after correcting for false discoveries, as compared to the traditional use of rolling averages of past returns. We obtain this result through a detailed analysis of the equity hedge UCITS funds' net returns using both the peer return style-factor and asset-based risk factor models over the period 2010–2016.

The rest of this chapter is organized as follows. Section 16.2 provides a review of the alternative UCITS market and the basic constructs used in a factor modeling approach. Section 16.3 describes the methodology and the data used in our empirical analysis. In particular, we describe the subuniverse of equity hedge UCITS funds and discuss factor selection. Section 16.4 describes our findings on disentangling the fund-specific residual performance from common style and asset-based factors. Section 16.5 then tests the out-of-sample performance of momentum-based fund-of-fund allocation based on residual returns. Finally, section 16.6 concludes.

16.2. Literature review

Alternative UCITS funds occupy a place in the investment space in between mutual funds and hedge funds. In this literature review, we first present a detailed definition of these investment vehicles. We then revisit important themes examined in prior research, such as risk-adjusted performance evaluation and biases that may arise when analyzing data sets of historical UCITS funds' net returns.

16.2.1. *UCITS fund structure*

The European UCITS is a pan-European regulation with the objective of harmonizing a regulatory regime across the European market, establishing a minimum level of investor protection requirements and facilitating cross-border marketing. The regulation encompasses the management and sale of retail investment funds that offer the unique return characteristics of hedge funds in an on-shore regulated vehicle with high liquidity and transparency. The format provides retail investors with access to a diverse range of underlying hedge fund strategies, such as long/short or momentum trading through managed futures [SEI 13, TUC 10, BUS 14].

UCITS was introduced in 1985 (85/611/EEC) to facilitate cross-border marketing and harmonize investor protection through product regulation (*viz*. transparency, investment guidelines and liquidity). The original UCITS directive only allowed for *transferable securities* (i.e. publicly traded equities or bonds listed on traditional stock exchanges). As a result from an industry call, the joint efforts in the UCITS III Directive (adopted in 2001), the commission recommendation in 2004 (2004/383/EC) and the Eligible Assets Guidelines in 2007 (CESR 07-044), allowed for a greater latitude in the investment spectrum and for sophisticated active management strategies to be packaged as UCITS [BUS 14, ARE 13]. Drafted in two parts, the Product Directive (2001/108/EC) – in combination with the Eligible Assets Guidelines – broadened the type and range of investments that UCITS can hold (financial derivatives for investment purposes, money instruments, cash deposits, etc.). One of the key characteristics of the directive permitted for a number of hedge fund strategies to be accommodated within the UCITS format. The *Management Directive* (2001/107/EC) provides funds with a European passport that enables them to operate throughout Europe once the investment fund is authorized in one member state[1].

In general, UCITS-compliant funds can offer nonlinear, hedge fund-like strategies in an regulated envelope, which is generally defined as an alternative UCITS fund. The fund structure is more constrained than a traditional hedge fund and simultaneously offers more flexibility than long-only vehicles. The main difference with traditional hedge funds is that they are subject to a number of strict guidelines related to risk management (e.g. investment restrictions, concentration limits and portfolio liquidity) and regulatory oversight. For example, UCITS-compliant funds are legally required to limit their leverage, they are prohibited from making large undiversified bets, they should focus on eligible instruments and investors can withdraw their money on – at least – a biweekly basis. Aside from being a stand-alone product, the structure also allows access to multiple underlying managers using an umbrella or a fund-of-fund structure. The popularity of the self-imposed constraints under the UCITS-framework is closely related to its perceived asset safety and transparency [WIE 13].

16.2.2. *Prior research on alternative UCITS*

A key research question in previous studies is focused on the cost of regulation. Or in other words, does UCITS-compliance lead to differences in risk-return characteristics between alternative UCITS funds and their off-shore unrestricted counterparts? Intuitively, we could expect that the impact of regulation limits the

1 For a more complete description on eligible assets, we refer to the council directives 85/61/EEC, 2001/108/EC, 2009/65/EC and 2012/832/ESMA and Chapter 2: *The UCITS Framework* in [BUS 14]. For a comprehensive discussion on risk management, leverage, concentration, counterparty and liquidity risk of alternative UCITS funds, we refer to [TUC 10].

flexibility of the manager. However, recent empirical work on the performance of the alternative UCITS fund manager provides mixed results.

In terms of risk-adjusted performance, [TUC 10, TUC 13] posit that UCITS funds should be less likely to show extreme returns under the common legal and regulatory framework. [TUC 10] look into cross-sectional differences between alternative UCITS indices and traditional hedge funds. Although they do not find conclusive evidence that orthodox hedge funds outperform alternative UCITS funds on a risk-adjusted basis, they do observe differences in risk, with UCITS funds showing a lower volatility. The authors attribute this to limitations on risk and leverage, higher liquidity and a lower attrition rate under the UCITS format. [BUS 14] compare equally weighted UCITS indices to matched hedge fund indices and asset-based factor models. They conclude that alternative UCITS are not perfect substitutes for hedge funds and show different risk profiles based on different loadings on systematic risk factors, a lower standard deviation and smaller tail risk. Additionally, [TUC 13] do not find statistically significant differences in mean performance compared to unrestricted funds. Yet, they do find that alternative UCITS funds have a lower exposure to illiquid assets than hedge funds. The dispersion of returns is investigated in [TUC 10], who suggest that performance in hedge funds is scattered over a more extensive range than in alternative UCITS. It is important to note that the authors inferred their conclusions on UCITS performance for the period between 2006 and 2010, when the investment vehicles were small in number.

16.2.3. *Data biases of alternative UCITS*

Our investigation of the performance of equity hedge alternative UCITS funds is empirical. An important caveat is that the data analyzed may be affected by a number of irregularities and biases that are often mentioned in the case of hedge fund data [JAG 10, FUN 97, FUN 01, FUN 04]. We summarize the most prominent database biases and discuss how they may also affect the reliability of alternative UCITS data.

First, a commonly cited problem when dealing with fund data is the end-of-life reporting bias, which occurs when a loss-making fund stops reporting its performance to database providers. This is similar to the self-selection bias inherent in hedge funds, where unregulated managers only have an incentive to report if the fund has done well. In the case of UCITS funds, this should be of little effect since UCITS requires reporting on a consistent basis.

Second, backfill bias or instant-history bias arises when a UCITS manager, entering a database, retrospectively backfills the fund's acquired performance track record. An inclusion of (non-representative) data prior to UCITS conformance can distort overall performance with favorable returns [BUS 14] or overestimation of managerial alpha in early years of the sample [JAG 10]. Still, the regulator allows past performance disclosure if there is no considerable difference [BUS 14]. It should also be taken into account that the associated history of UCITS is relatively short, as most UCITS funds were launched in the wake of the late-2000s crisis. Hence, an elimination of prior non-UCITS history would lead to a loss of (already scarce) data points and thus low power in testing [FUN 09, BUS 14].

Finally, survivorship bias implies that a database only reflects the returns generated by surviving funds, since poor performance (originating from dead funds) will be excluded from the study. Within hedge funds this seems to be a major issue. The market segment is characterized by high attrition rates as unsuccessful funds quickly liquidate [BUS 14]. On the other hand, in alternative UCITS research some authors assume non-existence following the notion that funds are obliged to report their performance [DEW 13, TUC 10, TUC 13] or provide an additional estimate of the magnitude of survivorship bias to account for potential malpractices [BUS 14][2]. In this chapter, we address the potential presence of a survivorship bias by collecting data for both extinct and alive funds in our sample of UCITS funds.

16.2.4. *Review of the factor model approach to study fund performance*

A central problem in fund selection is the evaluation of the risk-adjusted performance of a fund. The most common approach consists of estimating the risk-adjusted performance of a fund by calculating the intercept of a least squares regression of the fund returns on a series of risk factors, such as the equity risk factors in [CAR 97] or the hedge fund risk factors put forward by [FUN 01, FUN 04][3].

More precisely, let $\mathbf{f}_t$ be the $(K \times 1)$ vector of factors at time t and denote by $r_{i,t}$ the fund's i excess return at time t. The factor model approach then estimates the following regression:

$$r_{i,t} = \alpha_i + \boldsymbol{\beta}_i' \mathbf{f}_t + \varepsilon_{i,t} \qquad [16.1]$$

where the intercept α_i is usually interpreted as a measure of talent, $\boldsymbol{\beta}_i$ is the $(K \times 1)$ vector of factor exposures and $\varepsilon_{i,t}$ is the corresponding error term, for $t = 1, \ldots, T$. The alpha and beta parameters in [16.1] are typically estimated using ordinary least

2 [BUS 14] measure the difference in performance between two buy-and-hold portfolios, one which invests solely in the surviving funds and one which allocates funds equally to the union of dead and surviving funds. The difference between the two portfolios is interpreted as the overestimated return resulting from a survivorship bias.

3 For presentation purposes, we focus on the fund's alpha as the risk-adjusted performance measure. However, it is straightforward to apply the regression in a peer performance evaluation framework with other risk-adjusted performance measures, such as the fund's (modified) Sharpe ratio, by using the equal-performance test of [LED 08] and [ARD 17].

squares. When the estimated alpha is significantly different from zero, the fund is classified as talented. This test is usually implemented using the heteroscedasticity and autocorrelation robust (HAC) standard error estimators of [AND 91] and [AND 92]. We refer the reader to section 16.3.2 for the exact factor specification.

16.3. Data and methodology

We analyze the performance of the equity hedge UCITS funds over the period January 2010–September 2016. This section describes the composition of the universe and zooms in on the factor models under consideration.

16.3.1. *Data*

For the composition of the alternative UCITS universe, we use the LuxHedge database, which provides us with a unique list of 1,434 funds[4]. The net asset values (NAV) and AuM were collected from Bloomberg.

In order to obtain a universe that is representative of the investable equity hedge UCITS universe, we applied a set of screening criteria. First, it is common that funds launch different share classes addressed to different classes of investors [BUS 14, COG 13]. We only keep one share class per fund. Second, non-Euro denominated share classes are converted into the same base currency using the end-of-month exchange rate to analyze the universe from the viewpoint of a European investor [TUC 10, BUS 14, BUS 15]. Third, studies on hedge fund performance require at least 24 months of data [ACK 99, FUN 00]. Given that alternative UCITS-compliant funds are a relatively young market segment, the elimination of return histories is a costly loss of observations [BUS 14] and can introduce other biases [FUN 09]. We follow [BUS 14, BUS 15] and require a shorter minimum return history of 12 months of compliance under the UCITS-format. For the *ex post* performance evaluation of funds, we only retain those funds that have at least a track record of 5 years. As mentioned before, the exclusion of dead funds can lead to an overestimation of average performance [JAG 10]. We use the union of active and inactive funds to mitigate any survivorship biasing influences in our sample. Finally, we exclude duplicates and funds lacking consecutive returns, and consider only funds with an inception data before January 2014. The resultant sample is composed of 618 funds with daily returns spread over 16 different strategies. For the *ex post* and *ex ante* performance evaluation using factor analysis, we consider

4 The LuxHedge alternative UCITS database is one of the largest sources available on alternative UCITS funds. The Luxembourg-based data provider was established in 2012 and collects data on funds with inception dates going back to 1998. They collect qualitative data for alternative UCITS funds such as fund names, ISINs, share class and reported strategies. We refer the interested reader do http://www.luxhedge.com for more details.

discrete end-of-month total returns on the funds' NAV. Our sample period spans from January 2010 to September 2016, which coincides with the European sovereign debt crisis and shows partial overlap with previous studies on alternative UCITS performance [TUC 10, TUC 13, DEW 13, BUS 14, BUS 15].

Table 16.1 reports the number of funds in the total universe per style and per strategy available in the LuxHedge database. We also report the growth of the universe of the studied time period. In growth rates not reported in this study, we examine that the AuM showed consistent growth, while the increase in the number of funds stalled in the later years of the sample (Panel C).

***Panel A* – Composition of alternative UCITS universe**

Style	No. of funds	% Universe
All	618	-
Equity hedge	178	28.8
Relative value	149	24.1
Multiasset	147	23.8
Macro	124	20.1
Event driven	20	3.2

***Panel B* – Style breakdown**

Strategy	No. of funds	% Universe
Fixed income arbitrage	134	21.7
Global Macro	79	12.8
Multi-Strategy	64	10.4
Fund of funds	59	9.5
Equity market neutral	59	9.5
Long/short Europe	58	9.4
Long/short global	36	5.8
CTA/managed futures	34	5.5
Volatility arbitrage	16	2.6
Convertibles arbitrage	15	2.4
Long/short emerging markets	14	2.3
Merger arbitrage	13	2.1
Long/short US	11	1.8
Currency arbitrage	11	1.8
Commodity arbitrage	8	1.3
Event driven	7	1.1

***Panel C* – Growth of alternative UCITS universe**

Month – Year	No. of funds	% Growth
January 2010	260	-
January 2011	337	29.6
January 2012	435	29.1
January 2013	516	18.6
January 2014	598	15.9
January 2015	616	3.0
January 2016	616	0.0

Notes: Table 16.1 gives an overview of our constrained set of alternative UCITS funds. Panel A presents the breakdown per style, in which multiasset represents strategies that did not have an appropriately matched HFRU strategy (i.e. commodity arbitrage, fund of funds, volatility arbitrage and multistrategy). Panel B presents the breakdown per self-reported strategy in descending order. Panel C presents the year-on-year growth of funds for the total sample period. The input data for this table was retrieved in October 2016.

Table 16.1. *LuxHedge alternative UCITS subuniverse (October 2016)*

Recall that in our study, we focus on equity hedge-inspired strategies. These strategies invest in liquid instruments with (in most cases) a daily pricing. They can invest in any sector, market capitalization, region or country. As a result, it is relatively practicable to accommodate them in a UCITS format [ANG 16]. We focus on a long/short UCITS aggregate index (*viz.* equity hedge), long/short global, long/short europe, long/short US and long/short emerging markets. We also identify an equity market neutral strategy. The main difference between a long/short and a market neutral strategy is that the first does not seek a neutral position in terms of market risk (beta neutral) and generally has a long bias. Consistent with previous studies, we construct equally weighted portfolios to represent the respective styles and strategies. We assume that investors allocate funds equally to all surviving funds in a buy-and-hold portfolio for the total sample period. As a reference group we select the Hedge Fund Research (HFR) UCITS indices, which represents the overall composition of the UCITS-compliant universe[5].

We proceed by examining cross-sectional performance differences. The risk-return scatter plot presented in Figure 16.1 suggests a degree of heterogeneity in terms of risk and return when we consider the equity hedge style funds represented by their equally weighted portfolios. This becomes more clear if we look at Table 16.2, which presents summary statistics for the location, scale and shape of the equally weighted strategies and the matched HFRU strategies over the total sample period (2010–2016). For the equity hedge strategies, the annualized returns range from 2.17 to 4.61%. In addition, we observe varying degrees of risk, measured in terms of standard deviation. For example, we find a smaller volatility for equity market neutral (1.97%) as compared to long/short Europe (4.93%). Typical stylized facts for the return distribution of a hedge fund are asymmetry and heavy tails. Differently, for alternative UCITS we observe that the average fund has a negative skewness and a leptokurtic distribution. We refer to [SCO 80], who discuss the positive preference for odd moments (mean, skewness) and aversion to even moments (variance, kurtosis). In most cases, we reject the null hypothesis of normality based on significant P-values for the Jarque–Bera test.

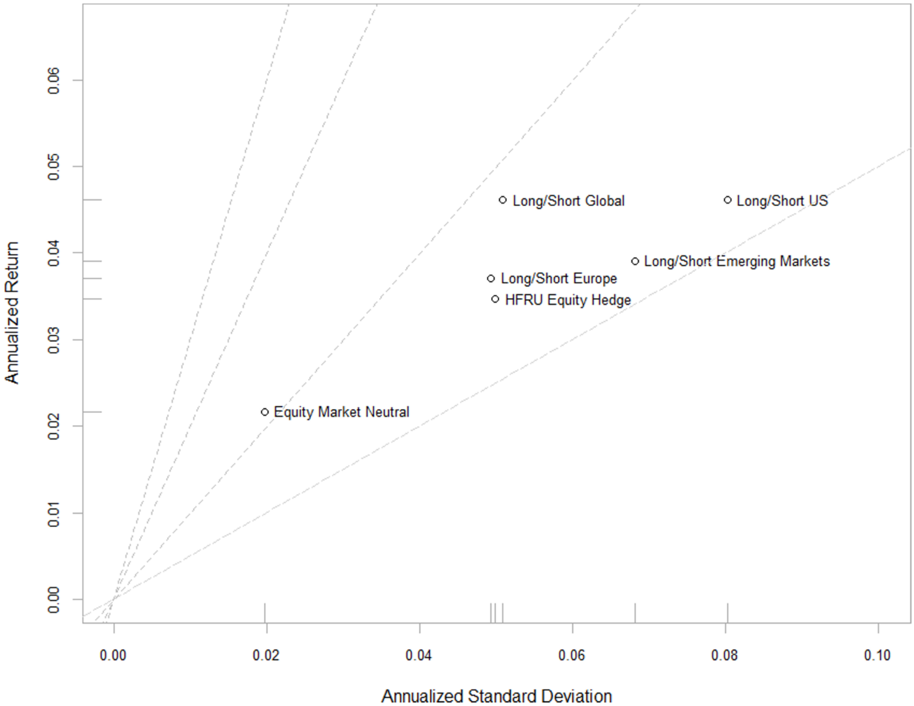
16.3.2. *Factor model specification*

In the sequel, we adjust returns for their factor exposure. Following the terminology of [FUN 97], our work is based on the notion that a manager's return can be characterized by three determinants, i.e. returns from assets in the portfolio, trading strategies and the use of leverage. Accordingly, a style-factor model is focused on a so-called location component (asset categories a manager invests in) and the asset-based risk factor approach refers to the strategy component (exposure to an asset class, direction and leverage).

The standard approach to model fund risk is to use broad-based indices as factors [FUN 04]. First, we identify the style benchmark market factors and look at excess return versus self-reported benchmarks. Next, we apply two baseline asset pricing models to separate the managerial alpha from identifiable risk factors: the common equity risk factors as proposed by [FAM 93, CAR 97] and the dynamic risk factors of [FUN 04]. The alpha describes the average performance of the fund above the return explained by the exposure to the systematic factors. All factors that we use in this

5 The Hedge Fund Research indices are comprehensive performance benchmarks for the total UCITS universe and include a composite index and four strategies, i.e. equity hedge, event driven, macro and relative value arbitrage. The indices are rebalanced on a quarterly basis (http://www.hedgefundresearch.com).

chapter can be interpreted as the returns on passive, zero-investment factor-mimicking portfolios [BAU 05].



Notes: Figure 16.1 presents a risk-return scatterplot of the equally weighted long/short strategies versus their style benchmark (i.e. HFRU Equity Hedge). The slope of the diagonal lines represent the Sharpe ratio for increasing values (i.e. 0.5, 1, 2 and 3).

Figure 16.1. *Annualized return and standard deviation for equity hedge UCITS (2010–2016)*

We evaluate the factor models at the level of synthetic indices, which pool all funds belonging to the same category, but also at the individual fund level. The relative performance of the former is affected by the variety in universe composition, since, as can be seen in Table 16.1, the number of constituents is not equal over different strategies, which can lead to extreme values and increased volatility measures [ZAN 12]. In their analysis, [BUS 14] report poor risk-adjusted performance in the form of alphas indistinguishable from zero (either statistically or economically) for the synthetic buy-and-hold portfolios. It is important to note that conclusions using the aggregate view cannot be generalized across the total population of managers, since the average of all fund returns is essentially the same as the benchmark [ANG 16]. Within alternative UCITS, [WIE 13] note that the quality of the operational set-up (for UCITS-compliance) and talent of managers may vary. Hence, fund selection within a heterogeneous universe is important. The focal point in this book chapter is to consider the risk-adjusted performance on a per-fund basis.

	(1) Ann. Return	(2) Ann. StDev	(3) Skewness	(4) Excess kurtosis	(5) Sharpe ratio	(6) Maximum drawdown	(7) JB p-value
***Panel A* – Alternative UCITS universe**							
Alternative UCITS	2.649	3.034	–0.423	1.025	0.873	5.001	0.053
Equity Hedge	3.345	3.650	–0.725	1.121	0.917	6.384	0.004
***Panel B* – Non-investable HFRU alternative UCITS indices**							
HFRU Composite	2.309	3.474	–0.771	0.891	0.671	6.226	0.005
HFRU Equity Hedge	3.474	4.993	-0.805	0.941	0.676	8.134	0.003
***Panel C* – Alternative UCITS equity hedge strategies**							
Equity Market Neutral	2.168	1.970	–0.516	1.259	1.100	2.675	0.014
Long/Short Global	4.615	5.092	–0.678	1.248	0.906	8.099	0.004
Long/Short Europe	3.707	4.928	–0.661	0.850	0.752	8.627	0.020
Long/Short US	4.607	8.021	–0.288	–0.380	0.574	15.353	0.471
Long/Short EM	3.908	6.812	–0.803	2.409	0.574	13.692	0.000

Notes: Table 16.2 presents the summary statistics over the total time interval (2010–2016) for our sample universe. For comparison, we also include the HFRU composite index as representative of the total UCITS universe. We report the annualized return (%), the standard deviation (%), sample skewness, sample excess kurtosis, Sharpe ratio, maximum drawdown (%) and the Jarque–Bera P-value. Panel A presents the results for two synthetic equally weighted composite and equity hedge portfolio. Panel B presents the results for the matched HFRU indices. Panel C presents the results for the equity hedge substrategies available in the LuxHedge database.

Table 16.2. *LuxHedge UCITS subuniverse: descriptive performance statistics*

16.3.2.1. *Peer return style-based factor model*

Jagannathan *et al.* [JAG 10] define a fund's relative alpha as the intercept in the regression of fund returns on the investment style returns to account for the common factors that affect all managers in the peer category. However, for the estimation of the peer alpha, we do not follow the methodology of these authors, who estimate the intercept with an aggregate US market factor, the self-reported style factor and an auxiliary factor based on statistical model selection. Instead, we will focus on the self-reported style index as an explanatory variable. In measuring the relative fund performance versus the self-reported style, we use equation [16.2]:

$$r_{i,t} = \alpha_i + \boldsymbol{\beta}_i r_{s,t} + \varepsilon_{i,t} \qquad [16.2]$$

where $r_{i,t}$ denotes the return in excess of the risk-free rate and $r_{s,t}$ is the self-reported style factor return.

In order to set up our style-factor model, we define our regressand as the equally weighted average return for all alternative UCITS funds within the same strategy. We choose the HFR indices for the representation of the alternative UCITS peer category. [BRO 03] note that the associated fund style is a strong determinant of the cross-sectional distribution in fund performance. This is also consistent with the observation in [HUN 14], who show that controlling for funds that operate under similar strategies tends to improve fund selection. Therefore, we consider these style indices as good proxies for nonlinear strategies of funds. We will first match the UCITS funds with their respective style axes to represent the market premium factor and the peer alpha. We acknowledge the matching will be imprecise in some cases, since funds self-report their strategies. As well as assessing overall management skills, we want determine whether there are stylistic differences. Or, in other words, are the return data consistent with the funds' reported investment style? In that connection, it is important to look at the goodness of fit (R^2). We refer to the substitution effect reported in [BUS 14], mutual fund selectivity in [AMI 13] and managerial talent in [TIT 11]. Suppose that the R^2 value is close to 1. In this case, the fund does not deliver any additional return and is fully exposed to the risk drivers of its representative benchmark.

16.3.2.2. *Asset return-based multifactor model*

A second approach consists of regressing the alternative UCITS fund returns onto a common risk factor space. The concept of factor investing is generally associated with long-only exposures to traditional equity risk factors, such as the value equity strategy [HAM 16]. When we use equity risk factors of the [CAR 97] model, we obtain the following linear factor model:

$$r_{i,t} = \alpha_i + \boldsymbol{\beta}_i^{mkt} r_{mkt,t} + \boldsymbol{\beta}_i^{smb} r_{smb,t} + \boldsymbol{\beta}_i^{hml} r_{hml,t} + \boldsymbol{\beta}_i^{wml} r_{wml,t} + \varepsilon_{i,t} \quad [16.3]$$

where $r_{i,t}$ denotes the return in excess of the risk-free rate, $r_{mkt,t}$ is the market return in excess of the risk-free rate, $r_{smb,t}$ is the return on small stocks minus return on large stocks, $r_{hml,t}$ is the return on high book-to-market values stocks minus return low book-to-market values and $r_{wml,t}$ is the return on winner stocks minus losers stocks over the last year. The data are provided on the Data Library of Kenneth French[6]. The risk-free rate is the local 1-month interbank offered rate.

Alternative risk premia are investments apart from long-only allocations to equity and bonds. These non-traditional risk premia correspond to nonlinear, long-short portfolios in equities, currencies, commodities or credit [HAM 16]. An alternative approach is to include nonlinear exposures in the set of risk factors with the objective of enhancing the risk-return analysis of funds and increasing our understanding of

6 http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/datalibrary.html.

the strategies implemented by these fund managers (viz. location, strategy and leverage)[7]. One could use the three option profiles put forward in [FUN 01] as regressors in the risk factor space to proxy the returns of dynamic trading strategies. In a follow-up study, [FUN 04] proposed a seven-factor model, which includes two equity factors, two bond factors and three nonlinear, trend-following strategies. These factors are generally accepted as the systematic sources of alternative risk premia for a balanced hedge fund:

$$\begin{aligned} r_{i,t} = \alpha_i + \boldsymbol{\beta}_{i,1} r_{mkt,t} + \boldsymbol{\beta}_{i,2} r_{smb,t} + \boldsymbol{\beta}_{i,3} r_{ge10y,t} + \boldsymbol{\beta}_{i,4} r_{spread,t} \\ + \boldsymbol{\beta}_{i,5} r_{ptfsbd,t} + \boldsymbol{\beta}_{i,6} r_{ptfsfx,t} + \boldsymbol{\beta}_{i,7} r_{ptfscom,t} + \varepsilon_{i,t} \end{aligned} \qquad [16.4]$$

Specifically for equity-oriented factors, we note that alternative UCITS funds invest in a regulated and a sufficiently liquid asset universe. [BUS 14] use the [FAM 12] global market (mkt) and global size (smb) factors instead of the excess returns of the S&P 500 (US aggregated market factor) and the difference between the Russel 2000 index and the S&P 500 index (size spread). The latter factors are commonly used in other papers as a reference to the original form of the seven-factor model. Following [BUS 14], we will use the international proxies for the respective factors and add back the 1-month US Treasury bill to adjust the excess returns. In order to capture a risk factor that is directed to fixed income instruments, we use the change in the iBoxx Germany 7-10 Government bonds ($ge10y$). For the credit risk factor in bond markets, we calculate the change in European credit spreads ($spread$), which is the difference between the yield of liquid investment grade bonds (i.e. iBoxx Euro Corporate Bond Euro AA 7-10 Year Index) and German government bond index. Regarding nonlinear strategies, there is strong empirical evidence on the time variation in hedge fund returns. These funds change their investment bets depending on changing market conditions and risk exposures [FUN 04, PAT 13]. In order to capture the nonlinear pay-off structure of equity-hedge strategies, we draw insights from trend-following strategies. [FUN 01, FUN 04] posit that momentum strategies behave like a long position in a lookback straddle and propose the Primitive Trend-Following Strategy (PTFS) on various asset classes to capture the essential features in trend-following funds' trading strategies, such as strong positive skewness and positive returns during market downturns[8]. The authors propose three drivers to proxy alternative risk premia: the $ptfsbd$ is the excess return on a bond lookback straddle, $ptfsfx$ is the excess return on a currency lookback straddle and $ptfscom$ is the excess return on a commodity lookback straddle. The data can be retrieved from the Data Library of David Hsieh[9]. Finally, $\epsilon_{i,t}$ is a mean zero error term. Contrary to

7 For a comprehensive elaboration on the mechanisms of alternative risk premia and market anomalies, we refer to [HAM 16, **?**].

8 Trend followers face frequent small losses and large gains. For a further discussion, we refer to [HAM 16].

9 https://faculty.fuqua.duke.edu/dah7/HFData.htm.

[BUS 15], the relevant factors in the model are converted to the same base currency using end-of-month exchange rates in EUR.

16.4. The cross-section of factor exposures and residual performance

Before we can start selecting funds, we need to isolate the manager-specific component from common-factor performance using a peer return style factor or a portfolio invested in rule-based strategies capturing the asset-based risk factors. We study alpha characteristics – *ex post* – for the collective equity hedge subuniverse for the period 2010–2016.

16.4.1. *Style-based analysis*

We analyze the alternative UCITS fund returns at different levels of granularity, starting with synthetic indices aggregating the returns over pools of funds, and then proceed with individual fund performance.

16.4.1.1. *Collective UCITS performance*

Recall that we have constructed equally weighted portfolios to represent the respective styles and strategies in our UCITS-compliant subuniverse (see section 16.3.1). We will use these synthetic indices as a proxy for the performance of the average UCITS-compliant fund. In what follows, we will focus on equity hedge UCITS strategies and regress synthetic buy-and-hold portfolios on a non-investable HFRU style benchmark. For comparison, we also include a buy-and-hold portfolio for all alternative UCITS funds in our subuniverse (all UCITS) and perform a regression on the HFRU composite index. We report our regression results in Table 16.3.

The α_i in column (1) is the mean residual return of the screened subuniverse over the HFRU style benchmark. Since we are mainly concerned with the accurate estimation of the intercepts, we should also estimate the associated HAC standard errors [NEW 87]. The evidence in Panel A indicates that the alternative UCITS screened subsample was able to generate a positive (economically and statistically) significant monthly alpha equal to 0.066%. While the overall equity hedge style (i.e. over all strategies and all funds) was *on average* not able to provide additional performance on top of the broad-based style portfolio. Panel B shows us the results of the regression of two non-overlapping periods, i.e. time-varying alpha. We see that for both the total UCITS universe and the equity hedge style, significance disappears in the second half of our sample. On a strategy level (Panel C), all the strategies – with the exception of equity market neutral – produced alphas that are indistinguishable from zero, meaning that a different geographic focus was not able to deliver a significant alpha surplus. While an equity market neutral strategy (a

		(1) $\alpha_i(\%)$	(2) $t(\alpha_i)$	(3) β_i	(4) $t(\beta_i)$	(5) R^2
Panel A **– UCITS Composite and Equity Hedge versus non-investable style indices**						
All UCITS		0.066*	[1.740]	0.800***	[17.180]	0.821
Equity Hedge		0.099	[1.480]	0.613***	[10.490]	0.704
Panel B **– UCITS Composite and Equity Hedge: Two-period analysis**						
All UCITS	2010-2013	0.123**	[2.630]	0.743***	[13.450]	0.814
	2013 - 2016	0.012	0.190	0.834***	13.770	0.832
Equity Hedge	2010-2013	0.134*	[1.770]	0.840***	[8.810]	0.725
	2013-2016	0.072	[0.730]	0.973***	[10.680]	0.778
Panel C **– Equity Hedge UCITS strategies versus non-investable Equity Hedge style index**						
Equity Market Neutral		0.123**	[2.214]	0.196***	[4.909]	0.247
Long/Short Global		0.134	[0.140]	0.859***	[12.707]	0.709
Long/Short Europe		0.065	[0.486]	0.841***	[12.872]	0.726
Long/Short US		0.248	[0.343]	0.524**	[2.550]	0.106
Long/Short E.M.		0.057	[0.289]	0.955***	[5.337]	0.489

Notes : Table 16.3 reports the results of the style factor regressions of synthetic equally weighted alternative UCITS portfolios versus the matched HFRU style indices. We use the HFRU composite for the synthetic composite index (All UCITS) and the HFRU equity hedge for the equity hedge style index and the long/short substrategies. The results in Panel A and C are measured over the entire sample period (January 2010–September 2016). Panel B reports results for two non-overlapping samples: (1) January 2010–May 2013; (2) June 2013–September 2016. Column 1 presents the estimated monthly alphas in percentages. Column 2 contains the *t* -statistics of two-sided tests of alpha, where the null hypothesis is that the alpha is zero. Column 3 presents the estimated betas against the respective HFRU style indices. Column 4 contains the *t*-statistics of the test that beta is zero. Column 5 shows the coefficient of determination (R^2). *, ** and *** denote statistical significance at the 10%, 5% and 1% level using heteroscedasticity and autocorrelation consistent standard errors following [NEW 87].

Table 16.3. *Regression results style-based factor model: synthetic portfolios (2010–2016)*

strategy that seeks a neutral position in the market) is able to deliver additional performance as compared to its overall peer category.

The coefficient of determination R^2 in column (5) indicates for the equity hedge style that the style index tends to fit our subsample data closely and makes up a considerable portion of our returns (70.4%). On a strategy level, the long/short Europe and long/short global strategies seem to move closely with the equity hedge peer category, showing a significantly positive β_i-coefficient (column 3) and high R^2. However, the difference in R^2 also shows us that there are stylistic differences between managers versus a peer benchmark. In other words, the equity hedge style benchmark is not able to capture all the nuances of the strategies. However, it is important to note that a low value for R^2 in the case of the long/short US and long/short emerging markets strategy is most likely due to a limited number of funds operating under the respective strategies (see Table 16.1). On average, the equity hedge style has a diminished beta, as indicated by an estimated β_i-coefficient of 0.613. The same observation holds for the other strategies.

	(1) N	(2) $\overline{\beta_i}$ $[\overline{SE_\beta}]$	(3) No. of significant α_i $at 5\%$	(4) $at 10\%$	(5) $\overline{R^2}$
Equity Hedge	101	0.618	15^+	20^+	0.229
		[0.168]	4^-	7^-	
Equity Market Neutral	35	0.214	8^+	8^+	0.093
		[0.132]	2^-	2^-	
Long/Short Global	14	0.998	2^+	3^+	0.328
		[0.229]	1^-	1^-	
Long/Short Europe	39	0.808	3^+	5^+	0.333
		[0.157]	1^-	4^-	
Long/Short US	6	0.488	1^+	3^+	0.120
		[0.231]	0^-	0^-	
Long/Short Em. Markets	7	0.882	1^+	1^+	0.217
		[0.221]	0^-	0^-	

Notes: Table 16.4 reports the significant alpha frequencies of the single style-factor regressions on individual alternative UCITS funds versus the peer group, i.e. the non-investable HFRU equity hedge. The results are measured over the entire sample period (January 2010–September 2016). Column 1 contains the number of constituents per strategy. Column 2 presents the average of estimated beta versus the HFRU equity hedge style index. The second row reports an average of the estimated standard error. Column 3 and 4 present the number of statistically significant alphas at the 5% and 10% level. The first row depicts the number of significantly positive alphas, the second row the significantly negative alphas. Column 5 presents the average R^2 of the style-factor model. The null hypothesis that the alphas are zero is tested using heteroscedasticity and autocorrelation consistent standard errors following [NEW 87]. We retained funds that had a track record of at least 5 years.

Table 16.4. *Alpha frequencies style-factor model: equity hedge funds (2010–2016)*

16.4.1.2. *Individual UCITS funds*

In the previous section, we inferred that our regression intercepts are (in most cases) indistinguishable from zero for the average equity hedge UCITS fund. Nonetheless, it is possible that good managers cancel out bad managers or that the synthetic portfolios may be subject to measurement errors in the independent variable (synthetic portfolio return), which makes the (average) alphas reported in our own and previous studies close to zero. In other words, a portfolio considering all managers may be inefficient as it ignores heterogeneity in the talent of fund managers. Individual managers may show traits that differ from the population. Moreover, descriptive statistics in Table 16.2 also point to non-normality (Jarque-Bera P-value), negative skewness and positive excess kurtosis in the fund returns, which jointly provide strong motivation for assessing individual fund performance and the role of talent in the industry. Table 16.4 summarizes the frequencies of significant alphas. We divide the observations into positive and negative significant excess returns at the 5% and 10% level. A positive and significant estimation for alpha signals a fund with superior talent compared to its peer category [JAG 10].

We observe a small number of funds that are able to generate significant excess returns compared to peers. Out of 101 equity hedge funds, 15 funds are positively significant at the 5% significance level and 20 at the 10% level. The analysis shows that we can select funds that demonstrate superior performance over the total sample period.

16.4.2. *Risk factor analysis*

In order to obtain more information on the relation between alternative UCITS and the equity market, we perform a risk-based analysis using equity risk factors. Compared to the previous section, we consider an asset-based factor model instead of a return-based approach. Table 16.5 presents the risk-adjusted returns of synthetic UCITS portfolios using the [CAR 97] four-factor model that considers equity-market factors (e.g. market, size, value and momentum).

16.4.2.1. *Collective UCITS performance*

The results in Table 16.5 show no evidence to reject the null hypothesis of an alpha indistinguishable from zero (column 1). In terms of $adj.R$ (column 6), we observe that the factors explain a high portion of the average returns of synthetic indices. To the extent that there are common factors that affect all managers in the UCITS universe, we find strong significance for the equity market factor (mkt) and the equity size factor (smb) in the total UCITS universe and the equity hedge funds. Moreover, all equity hedge substrategies load significantly on the equity market factor (mkt) and in most cases on the equity size factor (smb). The long/short US strategy also shows exposure to the value (hml) and momentum factor (wml).

We can look at the relation of synthetic UCITS portfolios and the [FUN 04] factor model in another way. We control for the relation to the global equity market (mkt), the global size factor (smb), the European bond market, the European credit spread and three trend-following, alternative risk premia represented by lookback straddles on bonds ($ptfsbd$), foreign exchange ($ptfsfx$) and commodities ($ptfscom$). The statistical results of the excess returns over the full sample period can be found in Table 16.6.

For the overall UCITS market, the most informative variables are the global equity market risk (mkt), global size (smb), the European bond factor ($ge10y$) and the European credit spread ($spread$), which validates our choice of focusing on global market factors instead of the traditional US-based factors. The significant loading on the European bond market may be due to the home bias discussed in [BAU 05]. It may be the case that UCITS-compliant funds – as a European format – overweight their positions in Europe. We do not find any evidence of significant factor loadings on the nonlinear factors across strategies. This observation is consistent with previous findings in [AGA 09, TUC 13, BUS 14], who note that alternatives are less exposed to classical alternative risk premia targeted by hedge funds. We also confirm previous observations of an alpha that is indistinguishable from zero, with the exception of the overall UCITS index.

	(1) $\alpha_i(\%)$	(2) β_{mkt}	(3) β_{smb}	(4) β_{hml}	(5) β_{wml}	(6) $adj.R^2$
***Panel A* – UCITS styles**						
All UCITS	-0.051	0.242***	0.056**	0.006	-0.006	0.789
	[1.216]	[16.421]	[2.099]	[0.32]	[0.355]	
Equity Hedge	-0.045	0.288***	0.091***	-0.023	-0.010	0.763
	[0.794]	[15.085]	[2.77]	[0.78]	[0.447]	
***Panel B* – Equity Hedge UCITS strategies**						
Equity Market Neutral	0.047	0.098 ***	0.107***	-0.023	-0.006	0.518
	[1.092]	[7.513]	[3.929]	[1.11]	[0.283]	
Long/Short Global	-0.109	0.420***	0.064	-0.050	0.031	0.811
	[1.411]	[15.763]	[1.318]	[1.161]	[1.429]	
Long/Short Europe	-0.060	0.377***	0.062	-0.044	-0.042	0.658
	[0.68]	[11.536]	[1.083]	[1.016]	[1.022]	
Long/Short US	-0.175	0.338***	0.287***	0.196***	0.081**	0.800
	[1.323]	[8.162]	[3.772]	[3.748]	[2.095]	
Long/Short Em. Markets	-0.090	0.396***	0.205***	-0.034	-0.059	0.416
	[0.375]	[5.696]	[2.75]	[0.435]	[0.852]	

Notes: Table 16.5 reports the results of the regressions of synthetic equally weighted alternative UCITS portfolios versus the Global Carhart factor model that includes market, size, value and momentum. The results in Panel A and B are measured over the entire sample period (January 2010–September 2016). Column 1 presents the estimated monthly alphas in percentages. Column 2 presents the estimated betas versus the equity market factor [FAM 12]. Column 3 presents the estimated betas versus the equity size factor [FAM 12]. Column 4 presents the estimated betas versus the equity value factor [FAM 12]. Column 5 presents the estimated betas versus the equity momentum factor [CAR 97]. Column 6 shows adjusted coefficients of determination (R^2). We present the t-statistics of the two-sided tests, in which the null hypothesis is that the coefficients are zero, in the second row of each regression. *, ** and *** denote statistical significance at the 10%, 5% and 1% level using heteroscedasticity and autocorrelation consistent standard errors following [NEW 87].

Table 16.5. *Regression results Carhart four-factor model: synthetic portfolios (2010–2016)*

	(1) $\alpha_i(\%)$	(2) β_{mkt}	(3) β_{smb}	(4) β_{ge10y}	(5) β_{spread}	(6) β_{ptfsbd}	(7) β_{ptfsfx}	(8) $\beta_{ptfscom}$	(9) $adj.R^2$
***Panel A* – UCITS styles**									
All UCITS	-0.089**	0.224***	0.057***	0.106***	0.147***	0.000	0.003	0.000	0.827
	[1.899]	[12.834]	[3.613]	[3.2]	[3.807]	[0.01]	[0.82]	[0.285]	
Equity Hedge	-0.041	0.275***	0.077***	-0.001	0.040	-0.001	0.000	-0.002	0.753
	[0.638]	[11.681]	[3.474]	[0.023]	[0.683]	[0.173]	[0.096]	[0.612]	
***Panel B* – Equity Hedge UCITS strategies**									
Equity Market Neutral	0.049	0.087***	0.102***	-0.014	0.047	0.001	-0.004	0.001	0.511
	[1.022]	[5.109]	[6.246]	[0.359]	[0.911]	[0.377]	[1.225]	[0.296]	
Long/Short Global	-0.086	0.402***	0.071**	0.042	0.034	-0.004	0.003	-0.007	0.804
	[1.084]	[12.188]	[1.942]	[0.819]	[0.342]	[0.55]	[0.737]	[1.338]	
Long/Short Europe	-0.041	0.351***	0.021	-0.060	0.037	-0.004	0.001	-0.004	0.640
	[0.413]	[8.798]	[0.534]	[0.751]	[0.38]	[0.499]	[0.103]	[0.707]	
Long/Short US	-0.258	0.410 ***	0.420***	0.148	-0.179	0.009	-0.004	0.002	0.769
	[1.635]	[8.188]	[6.704]	[1.292]	[1.1]	[0.796]	[0.355]	[0.272]	
Long/Short Em .Markets	-0.150	0.373***	0.104	0.149	0.109	-0.007	0.014	-0.007	0.408
	[0.571]	[4.129]	[1.588]	[1.183]	[0.618]	[0.585]	[1.638]	[0.628]	

Notes: Table 16.6 reports the results of the Fung and Hsieh seven-factor regressions of synthetic equally weighted alternative UCITS portfolios versus the [FUN 04] factors: global equity market, global size factor, European bond market, European credit spread and three trend-following lookback bond straddles (bond, foreign exchange and commodities) The results in Panels A and B are measured over the entire sample period (January 2010–September 2016). Column 1 presents the estimated monthly alphas in percentages. Column 2 presents the estimated betas versus the global equity market factor [FAM 12]. Column 3 presents the estimated betas versus the global equity size factor [FAM 12]. Column 4 presents the estimated betas versus a European bond-market factor. Column 5 presents the estimated betas versus a European bond credit spread factor. Columns 6–8 present the estimated betas versus the [FUN 04] trend-following factors in resp. bonds, foreign exchange and commodity. Column 9 shows adjusted coefficients of determination ($adj.R^2$). We present the t -statistics of the two-sided tests, in which the null hypothesis is that the coefficients are zero, in the second row of each regression. *, ** and *** denote statistical significance at the 10%, 5% and 1% level using heteroscedasticity and autocorrelation consistent standard errors following [NEW 87].

Table 16.6. *Regression results Fung and Hsieh seven-factor model: synthetic portfolios (2010–2016)*

	(1) N	(2) β_{mkt} $[SE_\beta]$	(3) β_{smb} $[SE_\beta]$	(4) β_{hml} $[SE_\beta]$	(5) β_{wml} $[SE_\beta]$	(6) No. of significant α_i $at5\%$	(7) $at10\%$	(8) $adjR^2$
Eq. Hedge	101	0.287	0.108	-0.004	-0.032	10^+	14^+	0.320
		[0.069]	[0.123]	[0.108]	[0.077]	7^-	11^-	
EM. Neutral	35	0.101	0.127	-0.022	-0.022	7^+	10^+	0.178
		[0.051]	[0.097]	[0.087]	[0.06]	2^-	2^-	
L/S Global	14	0.493	0.115	-0.010	-0.019	1^+	1^+	0.437
		[0.092]	[0.147]	[0.143]	[0.097]	1^-	3^-	
L/S Europe	39	0.360	0.038	-0.026	-0.053	2^+	2^+	0.357
		[0.073]	[0.132]	[0.132]	[0.082]	4^-	5^-	
L/S US	6	0.352	0.267	0.253	0.119	0^+	0^+	0.678
		[0.054]	[0.114]	[0.1]	[0.064]	0^-	1^-	
L/S Em. Mar.	7	0.374	0.221	0.002	-0.047	0^+	1^+	0.308
		[0.097]	[0.097]	[0.157]	[0.109]	0^-	0^-	

Notes: Table 16.7 reports the significant alpha frequencies of the Carhart four-factor regressions on individual alternative UCITS funds. The results are measured over the entire sample period (January 2010 - September 2016). Column 1 contains the number of constituents per strategy. Column 2 presents the average of estimated beta versus the global equity market [FAM 12]. The second row reports an average of the estimated standard error. Column 3 presents the average of estimated beta versus the global size factor [FAM 12]. Column 4 presents the average of estimated beta versus the global value factor [FAM 12]. Column 5 presents the average of estimated beta versus the global momentum factor [FAM 12]. Column 6 and 7 present the number of statistical significant alphas at the 5% and 10% level. The first row depicts the number of significantly positive alphas, the second row the significantly negative alphas. Column 8 presents the average R^2 of the Carhart four-factor model. The null hypothesis that the alphas are zero is tested using heteroscedasticity- and autocorrelation consistent Standard Errors following [NEW 87]. We retained funds that had a track record of at least 5 years.

Table 16.7. *Alpha frequencies Carhart four-factor model: Equity Hedge funds (2010-2016)*

When comparing Table 16.5 and 16.6, we notice that the Fung and Hsieh factors explains a higher portion of the variance in returns ($adj.R^2$) and possibly a better estimation of the intercept compared to the Carhart model. We report an improvement of the in-sample adjusted R^2 from 0.780 in the Carhart model (Table 16.5, column 6) to 0.827 in the Fung and Hsieh model (Table 16.6, column 9). Yet, we detect a deterioration for the equity hedge style and individual substrategies , with the exception of equity market neutral. Altogether, the analysis of both models does not present us with a conclusive picture on the incremental improvement of using the Fung and Hsieh alternative risk premia.

	(1) N	(2) β_{mkt} $[SE_\beta]$	(3) β_{smb} $[SE_\beta]$	(4) β_{ge10y} $[SE_\beta]$	(5) β_{spread} $[SE_\beta]$	(6) β_{ptfsbd} $[SE_\beta]$	(7) β_{ptfsfx} $[SE_\beta]$	(8) $\beta_{ptfscom}$ $[SE_\beta]$	(9) # significant α_i $at5\%$	(10) $at10\%$	(11) $adj R^2$
Equity Hedge	101	0.280	0.095	-0.021	0.013	-0.004	-0.001	-0.001	13^+	15^+	0.305
		[0.083]	[0.09]	[0.16]	[0.249]	[0.016]	[0.014]	[0.013]	7^-	11^-	
Equity Market Neutral	35	0.099	0.106	-0.045	-0.003	0.000	-0.009	0.003	8^+	8^+	0.176
		[0.063]	[0.065]	[0.122]	[0.179]	[0.013]	[0.011]	[0.01]	2^-	2^-	
L/S Global	14	0.475	0.091	0.040	0.058	-0.004	0.007	-0.004	0^+	1^+	0.393
		[0.102]	[0.118]	[0.183]	[0.324]	[0.021]	[0.018]	[0.017]	1^-	4^-	
L/S Europe	39	0.334	0.007	-0.061	0.029	-0.008	-0.001	-0.002	4^+	5^+	0.352
		[0.087]	[0.093]	[0.168]	[0.263]	[0.017]	[0.014]	[0.013]	4^-	5^-	
L/S US	6	0.388	0.518	0.113	-0.052	0.001	0.001	0.008	0^+	0^+	0.611
		[0.074]	[0.092]	[0.172]	[0.277]	[0.017]	[0.015]	[0.013]	0^-	0^-	
L/S Em. Markets	7	0.365	0.142	0.080	-0.024	-0.011	0.018	-0.008	1^+	1^+	0.235
		[0.128]	[0.128]	[0.234]	[0.335]	[0.022]	[0.018]	[0.02]	0^-	0^-	

Notes: Table 16.8 reports the significant alpha frequencies of the Fung and Hsieh seven-factor regressions on individual alternative UCITS funds. The results are measured over the entire sample period (January 2010–September 2016). Column 1 contains the number of constituents per strategy. Column 2 presents the average of estimated beta versus the global equity market [FAM 12]. The second row reports an average of the estimated standard error. Column 3 presents the average of estimated beta versus the global size factor [FAM 12]. Column 4 presents the average of estimated beta versus a European bond market factor. Column 5 presents the average of estimated beta versus a bond European bond credit spread factor. Columns 6–8 presents the average of estimated beta versus [FUN 04] trend-following factors in resp. bonds, foreign exchange and commodities. Columns 9 and 10 present the number of statistically significant alphas at the 5% and 10% level. The first row depicts the number of significantly positive alphas, and the second row the negative significant alphas. Column 11 presents the average R^2 of the Fung and Hsieh four-factor model. The null hypothesis that the alphas are zero is tested using heteroscedasticity and autocorrelation consistent standard errors following [NEW 87]. We retained funds that had a track record of at least 5 years.

Table 16.8. *Alpha frequencies Fung and Hsieh seven-factor model: equity hedge funds (2010–2016)*

16.4.2.2. *Individual funds*

In the previous section, we applied the Carhart four-factor model on synthetic equally weighted portfolios. For the average equity hedge UCITS fund, we did not find evidence to reject the null hypothesis of alphas indistinguishable from zero after accounting for the equity risk factors of the Carhart model. This observation remains consistent across substrategies. Next, we perform the regressions on a per-fund basis and thus investigate potential superior skill of individual funds after adjusting for market-wide equity risk factors. We report regression results in Table 16.7. We find that only a small number of managers produce significant alphas on top of the [CAR 97] asset-based factors over the total sample period. Within equity hedge, 10 funds out of 101 are able to produce a significantly positive alpha at the 5% level, and 14 at the 10% level, which is thus only slightly higher than the expected number of type I errors. The average estimates for β show that the equity hedge and equity market neutral strategy deliver almost beta neutral loadings to the market factor, 0.287 and 0.101.

In the analysis of the [FUN 04] model on synthetic buy-and-hold portfolios, we did not reject the zero-alpha hypothesis. Table 16.8 presents managerial performance after unbundling the returns using alternative risk factors inherent in hedge funds. We find evidence of statistically significant alphas for a small number of funds. This means that only a limited subset of managers show superior performance on top of the passive replicated portfolios that are augmented with the nonlinear Fung and Hsieh factors. Within equity hedge 13 funds out of 101 produce a significantly positive alpha at the 5% level, 15 at the 10% level.

Our decomposition of the universe reveals that the majority of the equity hedge UCITS funds are zero-alpha funds. We observe that less than 15% of managers (both at the 5% and 10% significance level) have managerial talent ($\alpha > 0$), while around 10% of managers are unskilled ($\alpha < 0$). However, a finding in which the majority of the funds is at par with systematic return sources is consistent with the findings in [BAR 10] for mutual funds.

However, we need to consider our results in the light of the statistical power of these tests. The analysis of simply counting the number of funds exceeding a preset significance level has the drawback that, when testing on multiple funds, it is prone to type I errors. In fact, when we use the usual significance levels of 5% (or 10%), we would expect that for 5% (or 10%) of the cases the zero-alpha funds will have a significant alpha measure. Conversely, in case of "bad" luck, funds with true significant alphas can have a test statistic in the region of non-rejection of the zero-alpha test [BAR 10]. In summary, significant residual performance is rare, but does exist.

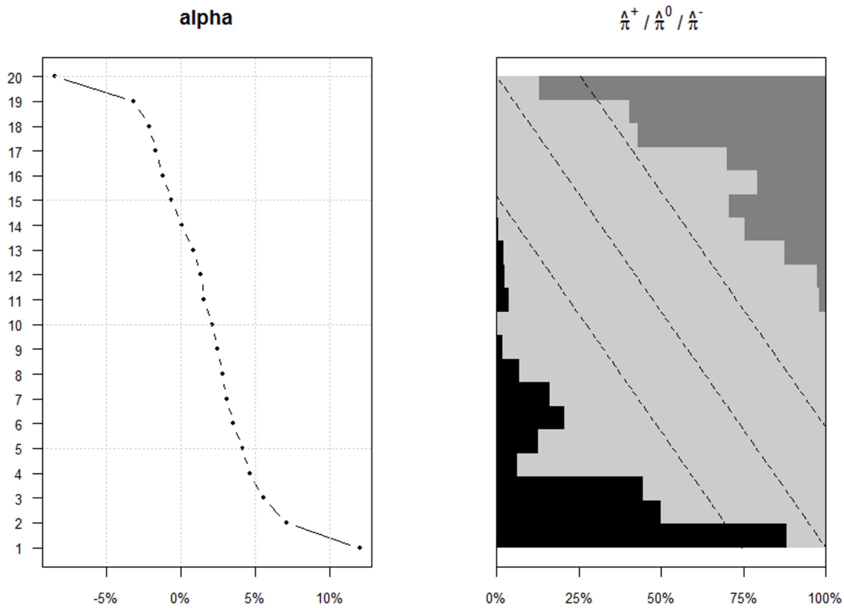
16.4.3. *Peer performance*

When the objective is to invest in quintile portfolios, the question of interest is not the number of funds with significant alpha, but to detect the funds that outperform their peers. The industry standard approach to evaluate an investment fund compared to its peers consists of two steps. First, we evaluate the focal fund using a standard performance measure, such as the Sharpe ratio or alpha. Next, the fund is ranked and percentiles are used to classify peer performance as either "outperforming" or "underperforming". Without regard to the possibility that funds show similar performance, this method may be prone to false discoveries. As a result, the performance evaluation may exhibit significant (estimated) alpha differentials between funds, while the true alpha is identical [ARD 17][10].

To address this problem, we propose evaluating the funds using the framework of peer performance, as proposed by [ARD 17]. The building block of this method is the "False Discovery" methodology by [STO 02] to obtain estimates of equal performance that are robust to false positives. We refer to [BAR 10] who provides an explicit form for estimators that are based on the false discovery rate and assesses the proportion of talented mutual funds. [ARD 17] provide an application in the hedge fund industry. The method evaluates an investment fund's performance by applying an evaluation framework that categorizes peer performance in three types: (1) equal performance ($\hat{\pi}^0$): the percentage composition of the peer group that perform as well as the fund of interest; (2) outperformance ($\hat{\pi}^+$): the percentage composition in the peer category the focal fund outperforms; and (3) underperformance ($\hat{\pi}^-$): the percentage of peer funds that outperform the focal fund.

In Figure 16.2, we show a two-panel diagnostic plot that examines the distribution of peer performance across funds. In the left plot, we ranked our universe by the average (annualized) monthly style-factor alpha. For example, Bucket 1 corresponds to the average of the best performing funds in terms of their style alpha. In the right barplot, we present for the corresponding buckets the average of estimated outperformance π^+ (black), equal-performance π^0 (light gray) and underperformance π^- (dark gray). While most funds show high values of equal performance to their peers, we still detect heterogeneity in the out- and underperformance ratios. Moreover, the alpha and peer performance outperformance ratio are in most cases positively nonlinearly dependent. This can be seen by the diagonal lines that accentuate the nonlinear relationship. For example, a 1% decrease in monthly alpha has a larger impact on the outperformance ratio for a top performing fund than a mediocre fund. In results not included in this study, we observed that the average downward correction for false discoveries is 37.2% for outperformance and 33.7% for underperformance as compared to a standard rank approach. It follows that the peer performance parameters account for estimation uncertainty in the associated performance measures.

10 The same authors make the comparison with the percentile-rank rate of outperformance and note that, in the extreme case of equal performance between all funds, the percentile-rank will be purely driven by noise.



Notes: A screening plot is a two-panel plot that examines the distribution of peer performance across funds. In the left plot, we rank the universe by (annualized) monthly style-alpha and group them in 20 buckets. In the right plot, we show, for each of the corresponding buckets, the average outperformance $\hat{\pi}^+$ (black), equal-performance $\hat{\pi}^0$ (light gray) and underperformance $\hat{\pi}^-$ (dark gray).

Figure 16.2. *Screening plot (2010–2016)*

Table 16.9 shows the ranking of funds based on their style factor alpha in column (1). Between brackets we show the outperformance and underperformance ratio for each focal fund. The last two columns show a comparison in ranking using the models proposed by [CAR 97] and [FUN 04]. First, we note the fairly broad scope in investment strategies that are in the top, middle or worst performers. It does not seem that a particular strategy has the upper hand when we use the style-factor alpha. Second, the factor models under consideration do not tend to give comparable rankings for the best and mediocre funds, with the exception of the two best funds that, respectively, follow a long/short emerging markets strategy and a long/short Europe strategy. Thus, the standard approach for estimating residual performance may be too optimistic about the outperformance of the focal fund. With regard to the worst funds, the models give consistent results.

In results not reported in this study, we computed the conditional probability of fund selection. While the factor models show comparable coefficients of determination on a collective level (see Tables 16.3, 16.5 and 16.6), they show different amounts of

Fund	(1) Strategy	(2) Style	(3) Carhart	(4) Fung and Hsieh
A	Long/short Em. markets	1[0.98; 0.00]	1[0.97; 0.00]	1[0.98; 0.00]
B	Long/short Europe	2[0.93; 0.00]	2[0.67; 0.00]	2[0.46; 0.00]
C	Long/short Global	3[0.85; 0.00]	60[0.00; 0.00]	10[0.00; 0.00]
D	Long/short US	4[0.77; 0.00]	50[0.00; 0.05]	20[0.06; 0.18]
E	Long/short US	5[0.86; 0.00]	64[0.00; 0.19]	32[0.10; 0.00]
...	...	...	...	...
K	Long/short global	50[0.00; 0.00]	57[0.00; 0.19]	42[0.00; 0.00]
L	Equity market neutral	51[0.00; 0.00]	43[0.00; 0.00]	34[0.15; 0.00]
M	Long/short Europe	52[0.00; 0.00]	58[0.00; 0.00]	43[0.00; 0.00]
N	Long/short Europe	53[0.09; 0.00]	46[0.38; 0.01]	31[0.33; 0.00]
O	Long/short Europe	54[0.00; 0.00]	17[0.26; 0.00]	55[0.00; 0.00]
...	...	...	...	...
V	Long/short Europe	99[0.00; 0.84]	102[0.00; 0.97]	98[0.00; 0.86]
W	Long/short Global	100[0.00; 0.82]	103[0.00; 0.87]	102[0.00; 0.82]
X	Long/short Global	101[0.00; 0.83]	99[0.00; 0.74]	103[0.00; 0.87]
Y	Long/short Europe	102[0.00; 0.93]	101[0.00; 0.82]	100[0.00; 0.86]
Z	Equity market neutral	103[0.00; 1.00]	100[0.00; 0.91]	101[0.00; 0.91]

Notes: Table 16.9 reports the alternative UCITS fund rankings for the fund's alpha with respect to the different factor models. We report the five best, five central and five worst funds in terms of the respective alphas. We report the ranking within the universe. In between brackets we show the outperformance and underperformance ratios with respect to different factor models. The alphas are calculated over the entire sample period (January 2010–September 2016). We retained funds that had a track record of at least 5 years (103 funds).

Table 16.9. *Peer performance and fund rankings*

coverage. Bearing in mind the fact that the factor models' intercepts proxy the fund's talent, they show different results in their ranking. For the style-factor model, we find the probability (conditional on a top ranking in the style-factor model) for the Carhart model and Fung and Hsieh model to be 62.0% and 49.4%, respectively.

16.5. Persistence of equity hedge UCITS managers

We now turn to our main research question regarding the equity hedge UCITS funds' alpha: Is there added value in factor model based estimation of residual performance for fund selection? This question is relevant since investors tend to shift their portfolio allocation to outperforming funds [FUN 08]. Therefore, we want to adopt a ranking criterion with a reliable signal of superior (relative) ability of a fund manager that integrates the use of risk premia in the bottom-up selection of fund managers [HAM 16]. The aim of this section is to verify the hypothesis of short-run persistence in performance using the residual return as a measure of managerial skill. This is related to the positive autocorrelation in monthly and quarterly mutual and hedge fund returns, which is known in the literature as the *hot hands* effect (see e.g.

P	Q	Equally-weighted portfolios Mean	Std	Sharpe	Alpha	Value-weighted portfolios Mean	Std	Sharpe	Alpha
***Panel A* – Benchmark Portfolios**									
S	–	3.877	4.063	0.893	–	3.192	3.777	0.780	–
***Panel B* – Portfolio sorts rolling using averages of past returns**									
M	Top	4.268	6.715	0.599	0.000	3.656	6.599	0.517	0.004
	Bottom	1.791	2.872	0.539	−0.020	2.887	2.417	1.093	0.113
MV	Top	3.210	4.400	0.674	0.030	2.627	4.070	0.586	0.006
	Bottom	1.320	2.929	0.368	−0.062	2.062	2.325	0.782	0.046
***Panel C* – Portfolio sorts using alpha**									
P	Top	6.240	5.778	1.036	0.298	5.210	5.951	0.834	0.238
	Bottom	1.977	5.496	0.316	−0.169	2.871	5.622	0.467	−0.089
C	Top	5.759	4.340	1.269	0.258*	4.966	4.554	1.036	0.198
	Bottom	3.710	6.866	0.504	−0.095	4.298	7.126	0.568	−0.049
F	Top	5.261	4.379	1.144	0.216	4.778	4.539	0.998	0.208
	Bottom	3.498	5.938	0.548	−0.075	4.693	6.125	0.726	0.024
***Panel D* – Portfolio sorts using t-statistic**									
P	Top	5.810	4.281	1.299	0.308*	5.250	4.604	1.086	0.268
	Bottom	1.432	5.227	0.228	−0.195*	2.203	4.727	0.414	−0.094
C	Top	6.203	3.581	1.662	0.334***	5.887	3.548	1.588	0.308***
	Bottom	2.978	5.915	0.462	−0.091	3.718	6.277	0.553	−0.039
F	Top	5.122	3.259	1.495	0.268**	4.983	3.271	1.447	0.268**
	Bottom	2.950	5.641	0.480	−0.095	4.100	5.487	0.702	0.017
***Panel E* – Portfolio sorts using out- and underperformance ratio**									
P	Top	5.963	5.500	1.038	0.301	4.757	5.508	0.819	0.205
	Bottom	1.427	4.733	0.250	−0.167	1.560	4.201	0.314	−0.126
C	Top	6.738	3.795	1.709	0.374***	6.413	3.864	1.595	0.349**
	Bottom	3.547	6.358	0.519	−0.075	4.781	6.697	0.677	0.013
F	Top	5.614	4.012	1.337	0.264**	5.317	4.135	1.225	0.266*
	Bottom	3.214	5.725	0.518	−0.075	4.014	5.738	0.656	0.005

Notes: Table 16.10 reports the results for an out-of-sample performance test of quintile portfolios using systematic momentum investment strategies based on style-factor model, the Carhart four-factor model and the Fung and Hsieh seven-factor model. We use equally weighted and value-weighted quintile portfolios. The evaluation period spans from December 2012 to September 2016. Panel A reports the results for synthetic benchmark portfolio (S) in which we include all the funds in our equity hedge universe. Panel B reports two systematic momentum strategies using only the return series of the fund. First, we look at a standard 36-month momentum strategy (M). We also include a momentum strategy which is scaled by volatility (MV). Panel C reports the alpha-sorted portfolios that selects funds based on the conditionally estimated intercepts by comparing fund returns with a factor space, respectively, the style or peer factor (P), Carhart four-factor model (C) and Fung and Hsieh's seven-factor model (F). Panel D reports the HAC alpha t -statistic portfolios that selects funds based on the significant HAC t -statistics of the estimated alphas in respective factor models. Panel E reports the out- and underperformance portfolios that select funds based on the peer performance ratios by [ARD 17] of the estimated alphas in respective factor models. We evaluate the quintiles based on annualized return (Mean, in %), annualized volatility (Std, in %), Sharpe ratio (Sharpe) and style-factor alpha (Alpha). *, ** and *** denote statistical significance at the 10%, 5% and 1% level using HAC standard errors.

Table 16.10. *Out-of-sample performance of quintile portfolios (2013–2016)*

[ARD 13, HEN 93, JAG 10]). We expect the set of outperforming funds to be time varying [AVR 11, CRI 14], which is consistent with the *adaptive market hypothesis* of [LO 04]. We do not consider the conditional nature of the alphas [JAG 10]. Still, we intend to show the practical relevance of common style and risk factors in the estimation using the standard approach discussed in [CAR 97, CAP 04] and [BLI 11] compared to systematic momentum techniques based on raw returns. We also address the question of the informativeness of the considered ranking criteria in peer performance evaluation. Of course, precise fund selection increases our odds of achieving persistently outperforming portfolios.

We proceed by analyzing whether past alpha is a predictor of future superior performance in the following way. On every selection date t we set up managed portfolios of alternative UCITS funds based on a ranking criterion of $t-1$. We account for the time variation in the distribution of monthly alphas by using 3-year rolling samples[11]. The out-of-sample evaluation ranges from December 2012 to September 2016 for a total of 46 rebalancing dates. The backtest considers 36 months of data in order to compute the alpha measures using the model discussed in equation 16.1. The ranking criteria under consideration are the unconditional alpha and two alternative ranking criteria. For the unconditional alpha, we assume that skilled funds are concentrated in the extreme tails. Thus, we infer that a high alpha provides a signal of fund manager skill. Nonetheless, unconditional alpha can be prone to measurement errors [JAG 10]. In implementing such a procedure, it is possible to mistakenly assign superior ability to managers and thus we also use the relative alpha t-statistic sorted strategy and the "false discovery" robust peer performance ratio. We proceed by composing equally weighted and value-weighted monthly rebalanced portfolios of the UCITS funds invested in the top and bottom quintile.

In order to assess the economic gains of selecting funds based on ranking criteria, we evaluate our portfolios using the annualized return, annualized standard deviation, Sharpe ratio and the style-factor alpha. The relevant questions are as follows: are we able to detect skilled funds over time and do we capture their superior alphas? How do we perform versus a synthetic market index and a systematic momentum strategy? We report our results in Table 16.10.

First, we verify that, across all sorting criteria, factor models and weighting methods, the difference in out-of-sample performance between the top quintile portfolio and bottom quintile portfolio is as we expected: the top quintile delivers a higher absolute return and higher risk-adjusted return as compared to the bottom quintile. We have to note that this is not the case for the value-weighted counterpart of a noise-driven momentum strategy, which shows a rather high standard deviation and a lower Sharpe ratio than the corresponding bottom portfolio.

11 We note that the previous analysis based on longitudinal time series may be unbalanced since the universe composition grows over time.

Second, a monthly rebalanced portfolio invested in the top quintile in terms of the alpha t-statistic and the outperformance ratio significantly outperforms the investing strategy based on the historical alpha. From a raw performance alpha perspective, we find that the winner (loser) quintile has a total return of 6.240 (1.977) percent and a Sharpe of 1.036 (0.316) for the alpha-sorted strategy. Comparable discrepancies can be found in the Carhart alpha and the Fung and Hsieh alpha. Conversely, investing in past winners using the t-statistics as a sorting criterion leads to a Sharpe ratio up to 1.662 with a corresponding significant style alpha. In relation to the outperformance ratio, we find a Sharpe ratio up to 1.709. It is interesting to see that the standard deviation is reduced when we use the alpha t-statistic or the outperformance ratio. Similar results are obtained in the case of alternative value-weighted schemes, which is more in line with an investable fund-of-funds strategy. We note a minor decrease in risk-adjusted performance, which indicates that our results are not driven by non-investable small funds.

Third, we detect a risk/return trade-off when using the t-statistic and outperformance ratio measures for selection: we can achieve a higher annualized return using the outperformance ratio at the cost of a higher standard deviation as compared to the alpha t-statistic. This is a finding which is consistent over all factor models.

Fourth, to the extent that we account for common factors that affect all funds in the universe, we can improve accuracy by controlling for the factors introduced by [CAR 97] and [FUN 04] as compared to the style-factor model. However, we do not find that the maximally expanded factor space delivers the highest performance. In all cases, the equity-inspired Carhart four-factor model delivers a higher risk-adjusted performance as compared to the Fung and Hsieh model. The observed performance further validates our use of factor models in performance persistence analysis.

16.6. Concluding remarks

The UCITS market is a fast-growing market segment within the fund management industry. In this chapter, we have studied the problem of identifying truly skillful managers. Despite the relevance of the topic, there are only a few empirical studies on the role of talent and alternative risk premia in the UCITS industry. We have contributed by reviewing the general characteristics of alternative UCITS funds and then zooming in on the performance of funds within a particular style, namely the equity hedge UCITS funds.

Foremost, it is important to consider the risk-return relationship. We examined the *ex post* risk-adjusted performance of alternative UCITS funds, taking into account a portfolio of systematic return sources (beta). At the aggregate index level, we report results consistent with previous research. We observe that studying average fund performance relative to the HFR style benchmark provides insights on the prevalence of talent in the UCITS-compliant universe. We find that the style index performs well in capturing the variance of the strategies operating under a common header. Furthermore, we observe the time-varying UCITS funds' alpha using two non-overlapping periods. Conversely, the analysis using the multifactor framework is less conclusive in explaining the main drivers of the UCITS industry. [BUS 14] conclude that the returns of alternative UCITS are less exposed to hedge fund risks. We support their finding by observing that the nonlinear, trend-following strategies of [FUN 04] do not show any incremental utility when considering the UCITS-compliant universe. Altogether, we believe more research is needed into the unbundling of returns using nonlinear strategies with different risk profiles and pay-outs [HAM 16].

The long-standing puzzle of active management skill is equally relevant in the UCITS universe. In order to complement literature, we also acknowledge the heterogeneity of the equity hedge UCITS universe by breaking down our returns in alpha and beta on a per-fund basis. Our decomposition of the universe reveals that a limited subset shows statistically significant alpha surplus after isolating the manager-specific component from the common-factor performance. The large proportion of unskilled zero-alpha funds might indicate that they are at par with the passive systematic betas. Based on standard significance tests, we find that significantly positive residual performance is rare in the analyzed equity hedge UCITS funds universe but does exist. Considering that the standard alpha significance test may not adjust for the possibility that performance may be due to chance, we apply a peer performance evaluation framework to adjust our findings for false discoveries. The adjustment can thus be considered as a reliable signal for fund-of-funds portfolio allocation. Further, while the intercepts of the factor models share a common goal, i.e. proxy the managerial talent of a particular fund, we find disagreement in fund ranking results across factor models.

Finally, we used an out-of-sample portfolio sort to detect performance persistence, following the notion that the choice of the skilled fund manager is based on his ability to reproduce superior past performance [JAG 10]. Using portfolio sorts, we show economic value in terms of a risk-return trade-off: we can achieve higher risk-adjusted returns when we control for false discoveries. However, the use of alpha t-statistics leads to lower-risk portfolios across both weighting schemes and factor specifications. Another takeaway is the decreased noise when using factor models in fund selection, which supports our aim of controlling for systematic return sources. It is important to remember that we are looking at relative performance persistence in the equity hedge universe. Altogether, the empirical results support our view that the proposed factor spaces and alternative ranking criteria are useful in the *ex post* evaluation of UCITS funds and the *ex ante* fund-of-funds investment strategies.

16.7. Bibliography

[ACK 99] ACKERMANN C., MCENALLY R., RAVENSCRAFT D., "The performance of hedge funds: risk, return, and incentives", *Journal of Finance*, vol. 54, no. 3, pp. 833–874, 1999.

[AGA 09] AGARWAL V., BOYSON N.M., NAIK N.Y., "Hedge funds for retail investors? An examination of hedged mutual funds", *Journal of Financial and Quantitative Analysis*, vol. 44, no. 2, pp. 273–305, 2009.

[AMI 13] AMIHUD Y., GOYENKO R., "Mutual fund's R2 as predictor of performance", *Review of Financial Studies*, vol. 26, no. 3, pp. 667–694, 2013.

[AND 91] ANDREWS D., "Heteroskedasticity and autocorrelation consistent covariance matrix estimation", *Econometrica*, vol. 59, no. 3, pp. 817–858, 1991.

[AND 92] ANDREWS D., MONAHAN J., "An improved Heteroskedasticity and autocorrelation consistent covariance matrix estimation", *Econometrica*, vol. 60, no. 4, pp. 953–966, 1992.

[ANG 16] ANGANA J., "The Rise of Indices is Changing the Face of Investing", S&P Dow Jones Indices, available at: https://us.spindices.com/documents/research/research-the-rise-of-indices-is-changing-the-face-of-investing.pdf, 2016.

[ARD 13] ARDIA D., BOUDT K., "The short-run persistence of performance in funds of hedge funds." in GREGORIOU G.N. (ed.), *Reconsidering Funds of Hedge Funds: The Financial Crisis and Best Practices in UCITS, Tail Risk, Performance, and Due Diligence*, Academic Press, Elsevier, 2013.

[ARD 17] ARDIA D., BOUDT K., The peer performance ratios of hedge funds, Working Paper, available at SSRN: https://ssrn.com/abstract=2000901, 2017.

[ARE 13] ARENDT & MEDERNACH, "Investment management: undertakings for collective investment in transferable securities (UCITS)", *Company Report*, pp. 1–50, 2013.

[AVR 11] AVRAMOV D., KOSOWSKI R., NAIK N.Y. *et al.*, "Hedge funds, managerial skill, and macroeconomic variables", *Journal of Financial Economics*, vol. 99, no. 3, pp. 672–692, 2011.

[BAR 10] BARRAS L., SCAILLET O., WERMERS R., "False discoveries in mutual fund performance: measuring luck in estimated alphas", *Journal of Finance*, vol. 65, no. 1, pp. 179–216, 2010.

[BAU 05] BAUER R., KOEDIJK K., OTTEN R., "International evidence on ethical mutual fund performance and investment style", *Journal of Banking & Finance*, vol. 29, no. 7, pp. 1751–1767, 2005.

[BLI 11] BLITZ D., HUIJ J., MARTENS M., "Residual momentum", *Journal of Empirical Finance*, vol. 18, no. 3, pp. 506–521, 2011.

[BRO 03] BROWN S.J., GOETZMANN W.N., "Hedge funds with style", *Journal of Portfolio Management*, vol. 29, no. 2, pp. 101–112, 2003.

[BUS 14] BUSACK M., DROBETZ W., TILLE J., "Do alternative UCITS deliver what they promise? A comparison of alternative UCITS and hedge funds", *Applied Financial Economics*, vol. 24, no. 14, pp. 949–965, 2014.

[BUS 15] BUSACK M., DROBETZ W., TILLE J., Can investors benefit from the performance of alternative UCITS?, Working Paper, Hamburg Financial Research Center Working Paper Series, no. 10, available at: http://www.hhfrc.de/fileadmin/user_upload/Website/Forschung/Working_Paper/HFRC_Working_Paper_Series_No13.pdf, 2015.

[CAP 04] CAPOCCI D., HÜBNER G., "Analysis of hedge fund performance", *Journal of Empirical Finance*, vol. 11, no. 1, pp. 55–89, 2004.

[CAR 97] CARHART M., "On persistence in mutual fund performance", *Journal of Finance*, vol. 52, no. 1, pp. 57–82, 1997.

[COG 13] COGNEAU P., DEBATTY P., HÜBNER G., "Predicting funds of hedge funds attrition through performance diagnostics", in GREGORIOU G.N. (ed.), *Reconsidering Funds of Hedge Funds: The Financial Crisis and Best Practices in UCITS, Tail Risk, Performance, and Due Diligence*, Academic Press, Elsevier, 2013.

[CRI 14] CRITON G., SCAILLET O., "Time-varying analysis in risk and hedge fund performance: how forecast ability increases estimated alpha", *Bankers, Markets & Investors*, vol. 123, pp. 5–15, 2014.

[DAR 14] DAROLLES S., "Evaluating UCITS compliant hedge fund performance", *Bankers, Markets & Investors*, vol. 133, pp. 11–22, 2014.

[DEW 13] DEWAELE B., MARKOV I., PIROTTE H. *et al.*, "Does manager offshore experience count in the alternative UCITS universe?", *Journal of Alternative Investments*, vol. 16, no. 1, pp. 72–85, 2013.

[FAM 93] FAMA E.F., FRENCH K.R., "Common risk factors in the returns on stocks and bonds", *Journal of Financial Economics*, vol. 33, no. 1, pp. 3–56, 1993.

[FAM 12] FAMA E.F., FRENCH K.R., "Size, value, and momentum in international stock returns", *Journal of Financial Economics*, vol. 105, no. 3, pp. 457–472, 2012.

[FUN 97] FUNG W., HSIEH D., "Empirical characteristics of dynamic trading strategies: The case of hedge funds", *Review of Financial Studies*, vol. 10, no. 2, pp. 275–302, 1997.

[FUN 00] FUNG W., HSIEH D., "Performance characteristics of hedge funds and commodity funds: natural vs. spurious biases", *Journal of Financial and Quantitative Analysis*, vol. 35, no. 3, pp. 291–307, 2000.

[FUN 01] FUNG W., HSIEH D., "The risk in hedge fund strategies: theory and evidence from trend followers", *Review of Financial Studies*, vol. 14, no. 2, pp. 313–341, 2001.

[FUN 04] FUNG W., HSIEH D., "Hedge fund benchmarks: a risk based approach", *Financial Analysts Journal*, vol. 60, no. 5, pp. 65–80, 2004.

[FUN 08] FUNG W., HSIEH D., NAIK N. *et al.*, "Hedge funds: performance, risk, and capital formation", *Journal of Finance*, vol. 63, no. 4, pp. 1777–1803, 2008.

[FUN 09] FUNG W., HSIEH D., "Measurement biases in hedge fund performance data: an update", *Financial Analysts Journal*, vol. 65, no. 3, pp. 36–38, 2009.

[GRE 13] GREGORIOU G.N., KAISERY D., PASCALAU R., "How geography, flows, and size affect the risk-adjusted performance of UCITS III funds of hedge funds", in GREGORIOU G.N. (ed.), *Reconsidering Funds of Hedge Funds: The Financial Crisis and Best Practices in UCITS, Tail Risk, Performance, and Due Diligence*, Academic Press, Elsevier, 2013.

[HAM 16] HAMDAN R., PAVLOWSKY F., RONCALLI T. *et al.*, A primer on alternative risk premia, Lyxor Asset Management, 2016.

[HEN 93] HENDRICKS D., PATEL J., ZECKHAUSER R., "Hot hands in mutual funds: short-run persistence of relative performance", *Journal of Finance*, vol. 48, no. 1, pp. 93–130, 1993.

[HUN 14] HUNTER D., KANDEL E., KANDEL S., *et al*. "Mutual fund performance evaluation with active peer benchmarks", *Journal of Financial Economics*, vol. 112, no. 1, pp. 1–29, 2014.

[JAG 10] JAGANNATHAN R., MALAKHOV A., NOVIKOV D., "Do hot hands exist among hedge fund managers? An empirical evaluation", *Journal of Finance*, vol. 65, no. 1, pp. 217–255, 2010.

[LED 08] LEDOIT O., WOLF M., "Robust performance hypothesis testing with the Sharpe ratio", *Journal of Empirical Finance*, vol. 15, no. 5, pp. 850–859, 2008.

[LO 04] LO A.W., "The adaptive markets hypothesis: market efficiency from an evolutionary perspective", *Journal of Portfolio Management*, vol. 30, no. 5, pp. 15–29, 2004.

[NEW 87] NEWEY W.K., WEST K.D., "A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix", *Econometrica*, vol. 55, no. 3, pp. 703–708, 1987.

[PAT 13] PATTON A.J., RAMADORAI T., "On the high-frequency dynamics of hedge fund risk exposures", *The Journal of Finance*, vol. 68, no. 2, pp. 597–635, 2013.

[SCO 80] SCOTT R.C., HORVATH P.A., "On the direction of preference for moments of higher order than the variance", *Journal of Finance*, vol. 35, no. 4, pp. 915–919, 1980.

[SEI 13] SEI, "The Retail Alternatives Phenomenon", SEI Knowledge Partnership, available at: https://www. seic.com/IMS/SEI-IMS-RetailAlternatives-US-2013.pdf, 2013.

[STO 02] STOREY J., "A direct approach to false discovery rates", *Journal of the Royal Statistical Society B*, vol. 64, no. 3, pp. 479–498, 2002.

[TIT 11] TITMAN S., TIU C., "Do the best hedge funds hedge?", *Review of Financial Studies*, vol. 24, no. 1, pp. 123–168, 2011.

[TUC 10] TUCHSCHMID N., WALLERSTEIN E., ZANOLIN L., "Will alternative UCITS ever be loved enough to replace hedge funds?", Working Paper, available at SSRN: https://ssrn.com/abstract=1686055, 2010.

[TUC 13] TUCHSCHMID N.S., WALLERSTEIN E., "UCITS: can they bring funds of hedge funds on-shore?", *Journal of Wealth Management*, vol. 15, no. 4, pp. 94–109, 2013.

[WIE 13] WIEDEMEIJER O., KELLER U., Alternative UCITS strategies – paradigm shift or expensive compromise?, Credit Suisse Asset Management, White Paper, available at: https://www.credit-suisse.com/pwp/am/downloads/marketing/whitepaper_am_afs_022013.pdf, 2013.

[ZAN 12] ZANOLIN L., "UCITS funds of hedge funds: the new Panacea?", in GREGORIOU G.N. (ed.), *Reconsidering Funds of Hedge Funds: The Financial Crisis and Best Practices in UCITS, Tail Risk, Performance, and Due Diligence*, Academic Press, Elsevier, 2012.

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Endorsements

Over the past years, factor investing has firmly established itself as an alternative approach to the investment process. The decreasing cost of smart beta exposure has not only spurred the shift in investment focus from assets to style (or risk) factors, but it has also fueled the desire to improve the efficacy of factor investing. This book with contributions from renowned academics and practitioners strikes a balance between theoretical rigor and practical relevance and pushes the boundaries of factor investing along multiple dimensions. The collected papers not only focus on novel factors (such as cross-asset carry and volatility risk premia, and factors in fixed income markets) and on how to best capture factor premiums, but they also discuss portfolio construction and risk control (neutralizing unwanted exposures and implementing volatility targeting), factor portfolio benchmarking, and extensions to long-short alternative risk premia investing. This comprehensive volume helps practitioners to keep abreast of the developments in this exciting field, providing them at the same time with practical guidelines to take factor investing to a next level.

Winfried Hallerbach, Director Quant Allocation Research (Robeco)

Factor based investing is clearly disrupting the asset management industry. This book, a second volume of selected recent research articles about factor investing edited by Emmanuel Jurczenko, has chapters written by leading academics and practitioners. Topics include factor selection, return predictability, portfolio construction, and include applications to both equity and alternative factors. Practitioners will find many implications for asset managers, asset owners, and for the industry as a whole.

Robert Litterman, Senior Partner (Kepos Capital)

Factor investing is a relatively novel approach to investment decisions which recommends that allocation decisions be expressed in terms of risk factors, as opposed to standard asset class decompositions. While the relevance of factor investing is now widely accepted amongst sophisticated institutional investors, an ambiguity remains, however, with respect to the exact role that risk factors are expected to play in the investment process. This book will definitely contribute to the widespread acceptance of factor investing by providing useful clarification with respect to various key aspects of factor investing in an institutional context. It is a must read for anyone interested in the efficient harvesting of traditional and alternative risk premia across and within asset classes.

Lionel Martellini, Director (EDHEC Risk Institute), Professor of Finance (Edhec Business School) and Senior Scientific Advisor (ERI Scientific Beta)

Changes in investment technology allow access to a large and growing set the of risk factors creating the building blocks for a new investment paradigm: risk factor investing. The road to practical implementation is however riddled with difficulties for the unsuspecting asset owner. Investors need to rethink and redevelop virtually all steps in their investment processes. Factor-benchmarking, -timing, -performance measurement, -selection, have no natural equivalent in the world of asset class investing. This book is an indispensable guide for asset owners and asset managers alike covering the newest thinking among leading academics and practitioners in the field. I enjoyed very much reading it, providing me new insights and ideas for both work as well as research.

Bernhard Scherer, Head of Private Wealth Management (Bankhaus Lampe) and Research Associate (EDHEC Risk Institute)

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Mathematics and Statistics

This new edited volume consists of a collection of original articles written by leading industry experts in the area of factor investing.

The chapters introduce readers to some of the latest research developments in the area of equity and alternative investment strategies.

Each chapter deals with new methods for constructing and harvesting traditional and alternative risk premia, building strategic and tactical multifactor portfolios, and assessing related systematic investment performances. This volume will be of help to portfolio managers, asset owners and consultants, as well as academics and students who want to improve their knowledge and understanding of systematic risk factor investing.

Emmanuel Jurczenko is Associate Dean and Professor of Finance at Ecole hôtelière de Lausanne, Switzerland. His research focuses on portfolio and risk management with a particular interest in risk budgeting, factor investing, and public and private equity real estate investments. Prior to joining Ecole hôtelière de Lausanne, he worked for ABN-AMRO between 2000 and 2006 as head of quantitative analysts, where he was in charge of quantitative fund selection.

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