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Alternative Equity Beta Investing: A Survey

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Alternative equity beta investing has attracted increased attention within the industry recently. Though products in this segment currently represent only a fraction of overall assets, there has been tremendous growth recently in terms of both assets under management and new product development. In this context, EDHEC-Risk recently carried out a survey[1] among a representative sample of investment professionals to identify their views and uses of alternative equity beta. This executive summary provides an overview of the background research, as well as the main results of this survey.

While "smart beta" is used broadly in the industry as a catch-all phrase for new indexation approaches that deviate from broad cap-weighted market indices, a recent trend is the appearance of factor indices that specifically target certain rewarded risk factors. In fact, the early generation of smart beta approaches (Smart Beta 1.0) aimed to either improve portfolio diversification relative to heavily concentrated cap-weighted indices (examples of such approaches are equal-weighting or equal-risk contribution, to name but two) or to capture additional factor premia available in equity markets (such as value indices or fundamentally-weighted indices, which aim to capture the value premium).

A potential shortcoming of focusing only on either improving diversification or capturing factor exposures is that the outcome, though improving upon broad cap-weighted indices, may be far from optimal. In fact, diversification-based weighting schemes will necessarily result in implicit exposure to certain factors, thus carrying the risk of unintended consequences for investors who may not be aware of the implicit factor exposures. Factor-tilted strategies, which do not consider a diversification-based objective, on the other hand, may result in highly concentrated portfolios to achieve their factor tilts. More recently, investors have started to combine both factor tilts and diversification-based weighting schemes to produce well-diversified portfolios with well-defined factor tilts, using a flexible approach referred to as Smart Beta 2.0. This approach, in particular, allows the design of factor-tilted indices (by using a stock selection based on factor-related stock characteristics) which are also well diversified (through the use of a diversification-based weighting scheme among the stocks with the desired factor exposures). Such an approach is also referred to as "smart factor investing" as it combines both the smart weighting scheme and the explicit factor tilt (see Amenc *et al.* (2014a)). More recently, investors have been increasingly turning their attention to allocation decisions across such factor investing strategies to generate additional value-added (see Amenc *et al.* (2014d)). The background section to our survey reviews the research on advanced beta equity strategies to provide a comprehensive discussion of potential benefits and risks, as well as implementation challenges with such strategies.

Investment practices in alternative equity beta strategies are currently evolving at a fast pace, in line with an increasing variety of product offerings, and our survey was thus not aimed at providing a definitive account of practices in this area. However, with offerings and communication by providers increasing, the discussion of such strategies rarely provides a buy-side perspective. Our survey aims to fill this gap and provide the investors' perspective on such strategies. In our survey, we prefer the term "alternative equity beta" to refer to such strategies. The objective of our survey was to gain

1 - Amenc, N., F. Goltz, V. Le Sourd, A. Lodh. 2015. Alternative Equity Beta Investing: A Survey. EDHEC-Risk Publication produced with the support of Société Générale Prime Services. The survey was conducted in 2014.

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insights into investor perceptions relating to such advanced beta equity strategies, but also into the current uses they make of such strategies. We cover both long-only strategies and long/short strategies but focus specifically on equity investments, and deliberately omit questions concerning alternative beta strategies in other asset classes. We asked respondents about their current use, familiarity, satisfaction, and future plans with alternative beta strategies. Moreover, we gathered information on the due diligence process and the quality criteria that investors use to evaluate such strategies and assess their suitability for their own investment context. Before turning to some key results from our survey, we briefly introduce the methodology below.

Survey Background: Alternative Equity Beta Investing

Index providers and asset managers have been prolific at creating alternative beta equity strategies which are systematic and transparent (as are cap-weighted equity indices), but which aim to generate outperformance with respect to standard cap-weighted indices. Various weighting schemes exist that try to improve diversification. In addition, various stock characteristics have been identified as being associated with above average returns. A key result of both the academic background to our survey, and the analysis of responses, is that tilts towards common equity risk factors play an important role in any advanced equity beta strategy. While we refer the reader to the full document for a detailed discussion of alternative weighting schemes, implementation issues, as well as common factor tilts, we focus here on the last aspect, of tilting towards various "factors".

Evolution of Multi-Factor Asset Pricing Models

Asset pricing theory postulates that multiple sources of systematic risk are priced in securities markets. In particular, both equilibrium models such as Merton's (1973) Intertemporal Capital Asset Pricing Model and arbitrage models such as Ross's (1976) Arbitrage Pricing Theory allow for the existence of multiple priced risk factors. This is in contrast to Sharpe's (1963) Capital Asset Pricing Model, which identified the market factor as the only rewarded risk factor. However, such models do not contain an explicit specification of what these factors are, having led some to qualify them as "fishing licenses" that allow researchers to come up with ever new data-mined factors, creating a whole "Factor Zoo." In order to avoid such factor fishing, which carries the risk of ending up with factors that matter a lot in the sample but do not persist, there should be fundamental economic reasons as to why a given factor should be rewarded in the long term. Thus, a key requirement for investors to accept factors as relevant in their investment process is related to the presence of a clear economic intuition as to why the exposure to this factor constitutes a systematic risk that requires a reward and is likely to continue producing a positive risk premium (see Ang (2014) and Cochrane (2000)). The survey background reviews the rationale for some of the widely used factors.

Empirical research has come up with a large variety of factors that explain differences in stock returns beyond what different levels of exposure to the market factor can explain. The literature documents that such additional factors have led to significant risk premia in typical samples of data from US and international equity markets.[2] Harvey, Liu and Zhu (2014) report that empirical

2 - These effects are often referred to as "*anomalies*" in the academic literature as they contradict the CAPM prediction that the cross section of expected returns only depends on stocks' market betas and should be void of any other patterns. However, when using a more general theoretical framework such as the intertemporal CAPM or Arbitrage Pricing Theory, there is no reason to qualify such patterns as anomalies.

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literature has identified more than 300 published factors that impact the cross section of expected stock returns. But not all of these factors present a sound economic rationale or more precisely a well-accepted risk-based explanation for their apparent risk premia.

In this summary, we focus on six of the most popular risk factors that indeed satisfy this condition and have therefore attracted immense attention in both academic and practitioner worlds alike – size, value, momentum, low risk, profitability and investment. Exhibit A summarises the various factor definitions and their corresponding literature references in various asset classes.

Rationale Behind Equity Risk Factors

While our background study discusses different empirical evidence of the presence of various factor premia, it also analyses explanations in the literature on why such factor premia exist. The existence of factor premia can be explained in two different ways – a risk-based explanation and a behavioural-bias explanation. The risk-based explanation premises that the risk premium is compensation to investors who are willing to take additional risk by being exposed to a particular factor. The behavioural explanation conceives that the factor premia exist because investors make systematic errors due to behavioural biases such as overreactions or under-reactions to news on a stock.[3]

A risk factor with a strong rational or risk-based explanation is more likely to continue to have a premium in the future. Therefore, it is perhaps more reassuring for an investor to have a risk-based explanation. In an efficient market with rational investors, systematic differences in expected returns should be due to differences in risk. Kogan and Tian (2012) argue that to determine meaningful factors "we should place less weight on the [data] the models are able to match, and instead closely scrutinise the theoretical plausibility and empirical evidence in favour or against their main

3 - Whether such behavioural biases can persistently affect asset prices is a point of contention given the presence of smart market participants who do not suffer from these biases. For behavioural explanations to be relevant, it is necessary to assume that – in addition to biases – there are so called "limits to arbitrage," i.e. some market characteristics, such as short-sales constraints and funding-liquidity constraints, which prevent smart investors from fully exploiting the opportunities arising from the irrational behaviour of other investors.

Exhibit A: Empirical Evidence for Selected Factor Premia: Overview and Key References

	Factor Definition	Within US Equities	International Equities	Other Asset Classes
Value	Stocks with high book-to-market versus stocks with low book-to-market	Basu (1977), Rosenberg, Reid, Lahnstein (1985), Fama and French (1993)	Fama and French (2012)	Asness, Moskowitz, and Pedersen (2013)
Momentum	Stocks with high returns over the past 12 months omitting the last month versus stocks with low returns	Jegadeesh and Titman (1993), Carhart (1997)	Rouwenhorst (1998)	Asness, Moskowitz, and Pedersen (2013)
Low Risk	Stocks with low risk (beta, volatility or idiosyncratic volatility) versus stock with high risk	Ang, Hodrick, Xing, and Zhang (2006), Frazzini and Pedersen (2014)	Ang, Hodrick, Xing, and Zhang (2009), Frazzini and Pedersen (2014)	Frazzini and Pedersen (2014)
Size	Stocks with low market cap versus stocks with high market cap	Banz (1981) Fama and French (1993)	Heston, Wessels, Rouwenhorst (1999) Fama and French (2012)	N.A.
Profitability	Stocks of firms with high profitability (e.g. return on equity) have high returns	Novy Marx (2013), Hou, Xue and Zhang (2014), Fama and French (2014)	Ammann, Odoni, and Oesch (2012)	N.A.
Investment	Stocks of firms with low investment (e.g. change in book-value) have high returns	Cooper, Gulen, and Schill (2008), Hou, Xue and Zhang (2014), Fama and French (2014)	Ammann, Odoni, and Oesch (2012); Watanabe, Xu, Yao, and Yu (2013)	N.A.

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economic mechanisms." This point is best illustrated by the example of the equity risk premium. Given the wide fluctuation in equity returns, the equity risk premium can be statistically indistinguishable from zero even for relatively long sample periods. However, one may reasonably expect that stocks have a higher reward than bonds because investors are reluctant to hold too much equity due to its risks.

We refer the interested reader to the complete document for a detailed discussion of the mechanisms that may lead to certain types of stocks (such as value stocks) being more risky, thus requiring a compensation for bearing this risk, or that may lead investor behaviour to lead to higher returns for such stocks. Exhibit B provides a brief overview of existing explanations.

To conclude, several risk factors have been empirically evidenced both in the US and on international equity markets and several economic explanations have been proposed in the literature. To be sure, there is uncertainty around these explanations, and the debate over why a given factor may carry a premium is ongoing for all the factors mentioned. However, having a convincing explanation should be a key requirement for investors when they decide to gain exposure to a given factor, as a theoretical justification of an observed effect provides some safeguard against data mining.[4]

This rich and evolving knowledge on factor premia in the academic literature provides a framework for actual factor investing practices. A main objective of our survey, after clarifying the academic background to such strategies, was to assess practitioner views and investment practices in the area. We now turn to a discussion of the results to the survey.

Survey Results: Use of Alternative Equity Beta Strategies and Perceptions of Investment Professionals

Methodology and data

The survey allowed us to collect the opinions of 128 respondents, largely representative of alternative equity beta users. The survey covers different parts of the world; however, European respondents were predominant

4 - We also note that the economic rationale is important because the measurement of risk premia is analysed based on an estimate of mean returns, which are notoriously hard to estimate reliably (see Merton (1980)) and thus naturally gives rise to debate in the literature. Several papers have discussed whether common factor premia such as small cap, momentum and value really exist in the data (see Fama and French (2012), McLean and Pontiff (2013) and Lesmond, Schill and Zhou (2004)). The analysis of an economic rationale goes beyond such difficulties.

Exhibit B. Economic Explanations for Selected Factor Premia: Overview

	Risk-based Explanation	Behavioural Explanation
Value	Costly reversibility of assets in place leads to high sensitivity to economic shocks in bad times	Overreaction to bad news and extrapolation of the recent past leads to subsequent return reversal
Momentum	High expected growth firms are more sensitive to shocks to expected growth	Investor overconfidence and self-attribution bias leads to returns continuation in the short term
Low Risk	Liquidity-constrained investors hold leveraged positions in low risk assets which they may have to sell in bad times when liquidity constraints become binding	Disagreement of investors about high risk stocks leads to overpricing in the presence of short sales constraints
Size	Low profitability leads to high distress risk and downside risk. Low liquidity and high cost of investment needs to be compensated by higher returns	Limited investor attention to smaller cap stocks
Profitability	Firms facing high cost of capital will focus on the most profitable projects for investments	Investors do not distinguish sufficiently between growth with high expected profitability and growth with low profitability, leading to under-pricing of profitable growth firms
Investment	Low investment reflects firms limited scope for projects given high cost of capital	Investors under-price low investment firms due to expectation errors

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as they represent two-thirds of the sample, while 16% of respondents were from North America and 17% from other parts of the world, including Asia Pacific, the Middle East, Africa and Latin America. The respondents to the survey were mainly asset managers (64%) and institutional investors (20%). The majority of respondents were also key investment decision makers, including board members and CEOs (12%), CIOs, CROs, heads of asset allocation or heads of portfolio management (31%), and portfolio or fund managers (27%). Respondents were mainly from large firms having over €10bn in assets under management (51%) or medium-sized companies with assets under management of between €100mn and €10bn (39%).

The Importance of Factors as Performance Drivers

According to respondents, the performance of alternative beta strategies is explained by factor tilts.[5] Thus, factors are seen as the main performance drivers for alternative beta, which underlines the notion that understanding the empirical evidence and economic rationale of such factors is of key importance. To a lesser extent, respondents also consider the performance of alternative equity beta strategies to be partly explained by rebalancing effects, as well as diversification.[6] Respondents are less convinced that the performance of alternative equity beta strategies is the result of data mining.[7] Value and small cap are the two factors considered by respondents as the most likely to be rewarded in the next ten years.[8]

Finally, according to respondents, the important characteristics for factor-tilted strategies are not only to provide the highest possible correlation with a factor, while maintaining neutral exposure to other risk factors, but also to provide the best ease of implementation at a low cost, and to achieve the best possible reward for a given factor. At the same time, it appears that current products are seen as inadequate for these requirements, with the worst score being obtained by the ability of current products to hedge undesired risk exposures.

Use of Alternative Equity Beta and Satisfaction Rates

From this survey, it appears that the main argument respondents have for using alternative equity beta is to gain exposure to rewarded risk factors, as well as to improve diversification relative to cap-weighted indices,[9] two arguments that are in accordance with the main criticisms of cap-weighted indices. Respondents also declare that they are strongly motivated by the potential of alternative equity beta strategies to provide lower risk and higher returns than cap-weighted indices, as well as by the transparency and low costs[10] of these strategies.

Respondents appear to be more familiar with long-only strategies than with long/short strategies. Consequently, the highest rates of investment, as well as the potential for increasing the investment in the future, are to be found among long-only strategies (see Exhibit C). 61% of respondents invest in low volatility and value strategies, and 52% of respondents invest in fundamental-weighted strategies, which were the strategies respondents indicate they were most familiar with. However, only 32% of respondents invest in the equal-weighted strategy, a naive strategy, though they are very familiar with it. The decorrelation/diversification approach appears to have potential for development in the future. While only 23% of respondents already invest in this type of strategy, 20% declare that they are likely to increase their investment in the strategy in the future, while another 22% are currently

5 - This argument was rated 1.04, on average, on a scale from -2 (totally disagree) to +2 (completely agree).
6 - These two arguments were respectively rated 0.39 and 0.27, on average, on a scale from -2 (totally disagree) to +2 (completely agree).
7 - This argument was rated -0.20, on average, on a scale from -2 (totally disagree) to +2 (completely agree).
8 - These two factors obtained a score of 3.28 and 2.93, respectively, on a scale from 0 (no confidence) to 5 (high confidence).
9 - These two arguments were respectively rated 1.22 and 1.13, on average, on a scale from -2 (strong disagreement) to +2 (strong agreement).
10 - These motivations were respectively rated 3.74, 3.50, 3.07 and 3.04, on average, on a scale from 1 (weak motivation) to 5 (strong motivation).

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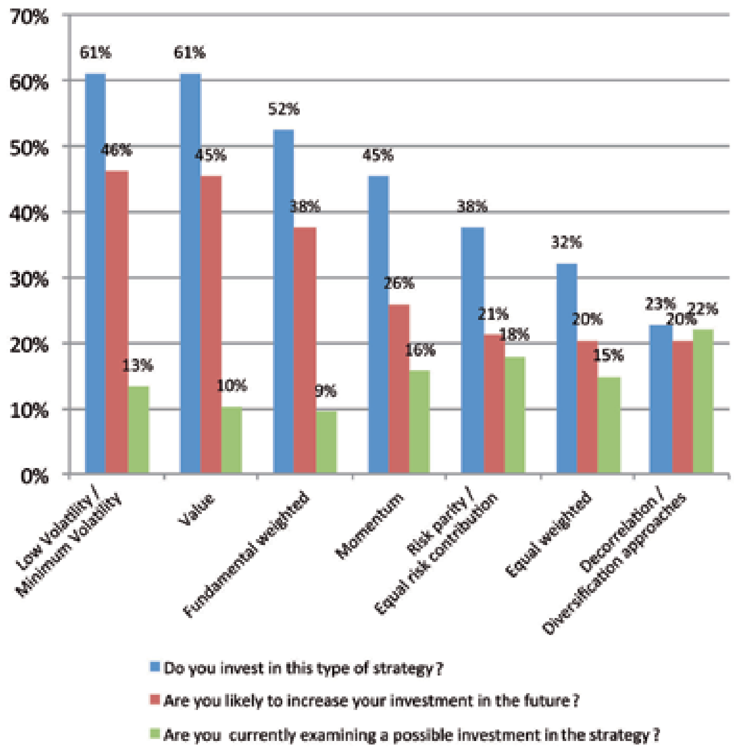
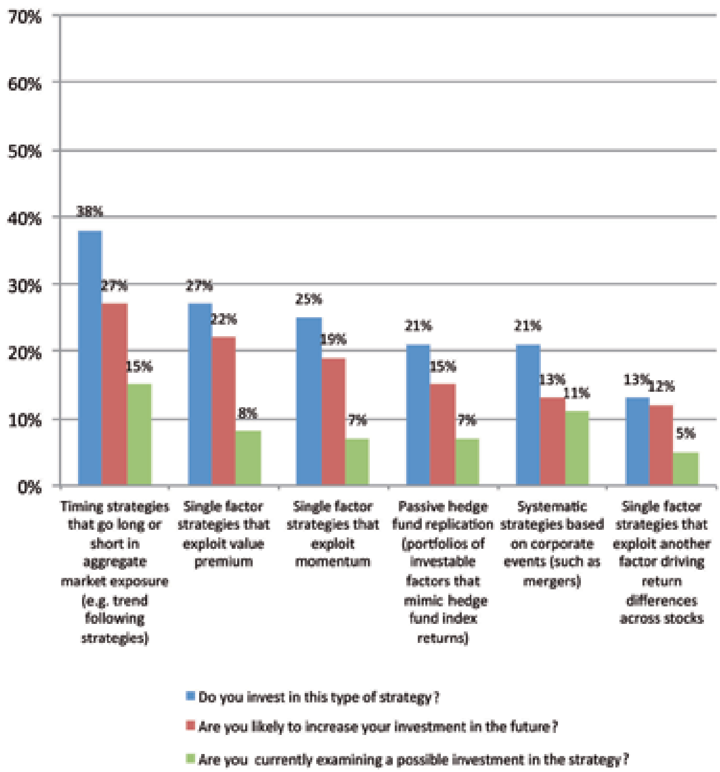
Exhibit C – Concerning your own investment in these types of strategies, please indicate for each of the following strategies your current status. – For each of the strategies, this exhibit indicates the percentage of respondents that already invest in it, together with the percentage of respondents that are likely to increase their investment in the future. It also shows the percentage of respondents that do not invest in the strategy at the present time, but are considering a possible investment in the future.





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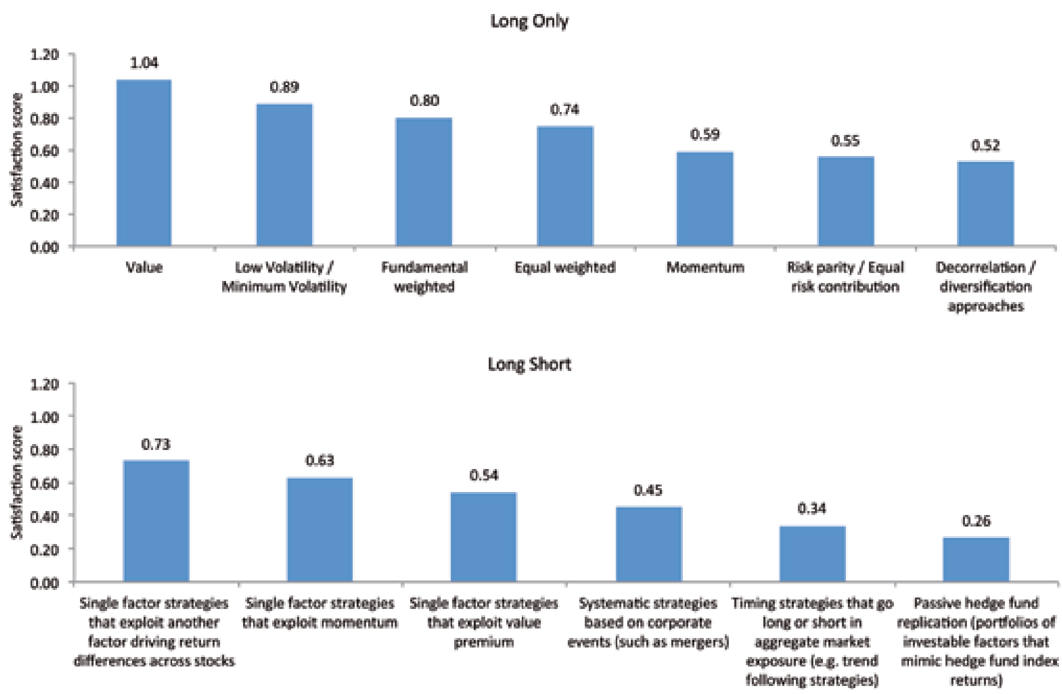
examining a possible investment in the strategy.

When asked to give their opinion about the current offering for the smart beta strategies that they declare they invest in, respondents credit all strategies, on average, with a positive rate of satisfaction (see Exhibit D). However higher satisfaction rates were obtained for long-only strategies, with the best score for the value strategy. In addition, long-only strategies respondents were the most familiar with received the highest rates of satisfaction, while the correlation between familiarity and satisfaction is not to be found among long/short strategies. For example, timing strategies were the ones respondents were the most familiar with, but the rate of satisfaction is one of the lowest among long/short strategies.

Challenges in evaluating and implementing alternative beta strategies

When they want to invest in alternative equity beta strategies, investors face different challenges that prevent them from investing more in alternative equity beta strategies. Not surprisingly, in view of the previous results, investors have better knowledge of evaluating and implementing long-only strategies, than long/short strategies (see Exhibit E). This relative lack of familiarity with long/short strategies is reflected in many additional and detailed results in our survey. Overall, it appears that investors feel that long/short strategies are too difficult to implement, and do not have extensive knowledge of these strategies or practical experience with investing in them. This is a notable difference with respect to long-only strategies, which are more widely used, and better understood by respondents according to their own account.

Exhibit D – Please indicate your satisfaction level with the following offerings – The satisfaction was rated from -2 (not at all satisfied) to +2 (highly satisfied). Only categories that respondents invest in according to their previous answers (see Exhibit B) are displayed. This exhibit gives the average score for each strategy.



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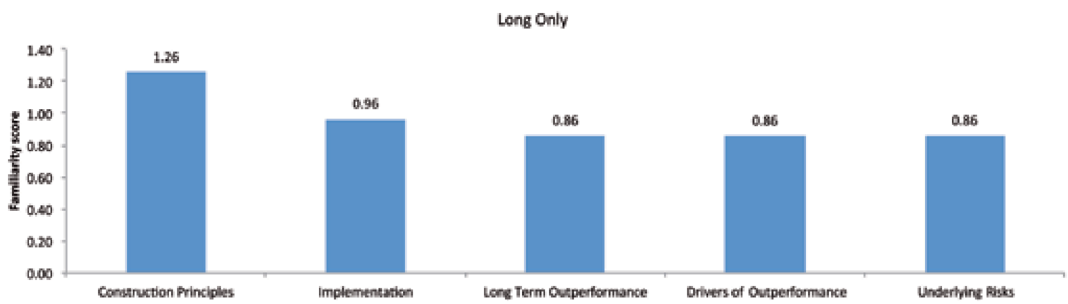
However, even for long-only strategies, it appears that investors are familiar with construction principles, but less familiar with underlying risks and drivers of performance, suggesting that providers do not offer a lot of information on performance drivers and risks.

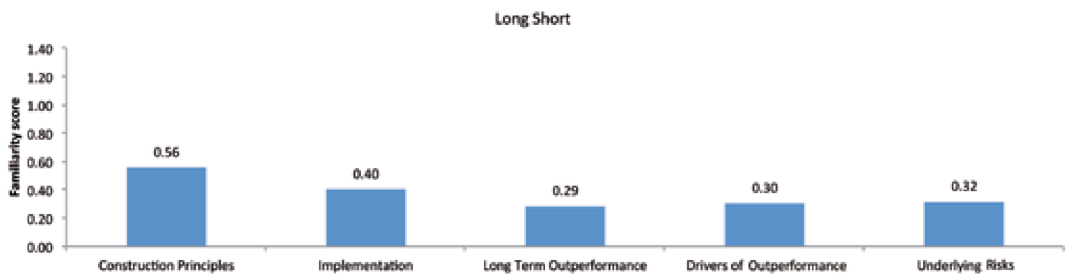
In addition, it appears from the survey that respondents allocate fewer resources for the evaluation of alternative beta compared to the evaluation of active managers. The evaluation of advanced beta offerings is firstly based on the use of independent research and on research published by providers, as well as on analytic tools, while meeting with providers is more important to evaluate active managers.

Respondents also see more challenges in evaluating smart beta offerings compared to active managers or cap-weighted indexing products. The lack of access to data, in particular live and after-cost performance, and the lack of transparency on the methodology are seen as key challenges. The evaluation of the risks of the strategies is also a big challenge in the evaluation process. Strategy-specific risks and specific risks related to factor tilts appear to be the most important risk sfor survey respondents, while the relative risk of underperforming cap-weighting indices periodically is the least important risk for them. Further, all respondents agree that information about risk is not widely available from product providers, whatever the risk dimension. Costs and transparency are crucial for respondents to evaluate strategies, and theoretical justification is about as important to them as live performance.

In terms of implementation, respondents agree that advanced beta has strong diversification potential in various strategies, but also assert that well-designed offerings for this use are not widely available yet,

Exhibit E – Which alternative equity beta strategies are you familiar with? For each alternative equity beta strategy, respondents were asked to rate each aspect, including construction principles, implementation, long-term outperformance, drivers of outperformance and underlying risks. The familiarity was rated from -2 (do not know about the topic) to +2 (very familiar). The exhibit displays the average score across all strategies.





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which prevents them from using alternative beta strategies in this way. It appears that respondents prefer long-only strategies to gain exposure to alternative risk premia, in particular due to perceived implementation hurdles for long/short strategies.

Key Challenges for Advanced Equity Beta Investing

Overall, our survey respondents' answers to an extensive questionnaire on their use of and perception of smart beta show that respondents have an overwhelming interest in advanced beta equity strategies. However, across the various sections of the questionnaire, respondents raised important concerns and several challenges regarding advanced beta investing in practice. While we refer the reader to the detailed document for a detailed discussion on the results of our survey, we try below to provide an overview of the main challenges. In fact, across answers to different questions in our survey, the following ten key conclusions emerge:

1. Investors are familiar with the construction principles of advanced beta strategies (rated 1.04, on average, on a scale from -2 (totally disagree) to +2 (completely agree)), but less familiar with underlying risks and drivers of performance (respectively rated 0.39 and 0.27, on average).[11]
2. Respondents allocate relatively few resources to the evaluation of alternative beta. The average respondent uses fewer than two full-time staff (1.77) to evaluate alternative beta offerings, a much lower number than that used to evaluate active managers (3.42).[12]
3. Respondents see bigger challenges with evaluating advanced beta offerings, with an average score of 3.21 on a scale from 1 (weak challenge) to 5 (very strong challenge), than with evaluating active managers or cap-weighted indexing products, with average scores of 2.02 and 2.87 respectively.[13]
4. Lack of access to data, rated 3.15, on average, on a scale from 1 (weak challenge) to 5 (very strong challenge), in particular live and after-cost performance, rated 3.63 and 3.34 respectively, on average, and analytics, rated 2.95 on average, are seen as key challenges.
5. For all types of risks, respondents agree that information is not widely available from product providers. The risk rated as the most important (risk related to factor tilt, rated 0.77, on average, on a scale from -2 (totally unimportant) to +2 (highly important)) is also one of those with the least information available according to respondents, who give a score of -0.10 on average to the availability of the information on a scale from -2 (strongly disagree that information is widely available) to +2 (strongly agree that information is widely available).[14]
6. Respondents' answers show that the theoretical justification of a strategy is seen as about as important as live performance, rated 1.14 and 1.24, respectively, on a scale from -2 (strongly disagree that it is important) to +2 (strongly agree) highlighting the need for product providers to focus not only on recent performance but also on the fundamental economic reasons for a strategy's performance benefits.[15]
7. Implementation is a key aspect for respondents, who commonly use a wide array of measures to assess implementation of alternative equity beta strategies (turnover, transaction costs, etc.), implying that product providers need to carefully consider implementation in product design[16].
8. Respondents prefer long-only strategies to gain exposure to alternative risk premia, in particular due to perceived implementation hurdles for long/short

11 - For each alternative equity beta strategy, respondents were asked to rate each aspect, including construction principles, implementation, long-term outperformance, drivers of outperformance and underlying risks.
12 - Respondents were asked for the number of full-time staff mainly concerned with the evaluation of advanced beta offerings, the evaluation of cap-weighted indices and passive investment products and the evaluation of active managers.
13 - Concerning the evaluation of investment strategies and products, including advanced beta offerings, cap-weighted indices and passive investment products and active managers, respondents were asked to indicate what they see as a challenge from among the following: lack of transparency on methodology, lack of access to data, lack of availability of live track records, lack of after-cost performance data, lack of availability of analytics and lack of availability of independent research.
14 - Respondents were asked to evaluate the relative importance of the various dimensions of risks in the assessment of alternative equity beta strategies and to give their opinion about the availability of information on each type of risk.
15 - Respondents were asked to indicate their agreement with the importance of a list of proposals concerning alternative equity beta strategies.
16 - Respondents were asked to indicate the measures they use to assess implementation aspects of alternative equity beta strategies.

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strategies. Long-only-tilted strategies obtained an average score of 1.01 for ease of implementation on a scale from -2 (weakly prefer) to +2 (strongly prefer), compared with 0.35 for long/short strategies.[17]

9. While respondents agree that advanced beta has strong diversification potential through various strategies, with an average score of 0.84 on a scale from -2 (strongly disagree) to +2 (strongly agree), they also agree that well-designed offerings for this use are not widely available yet, with an average score of -0.12 on a scale from -2 (strongly disagree) to +2 (strongly agree), which prevents them for using alternative beta strategies in this way.[18]

10. Respondents require more from factor investing strategies than simply providing the right direction of exposure, rated 1.24 on a scale from -2 (not at all important) to +2 (important), notably to provide an efficient risk-adjusted return for a factor exposure, rated 0.93, with ease of implementation, rated 1.17. Current products are seen as insufficient for these requirements, as the achievement by current products of these requirements are rated 0.49, 0.19 and 0.25, respectively on a scale from -2 (not fulfilled at all) to +2 (completely fulfilled).[19]

The robustness of the answers given by respondents in this survey was tested by considering the results by category of respondents, according to their activity, their country and the size of the company. Similar results were obtained whatever the category respondents belong to, proving that the results of this survey are quite robust, as they are not related to a specific category of respondents.

While our survey results suggest that advanced beta equity investing is a promising avenue for the investment industry, our results also contain a note of caution, in that there is a risk that the good idea of advanced beta equity investing may end up being compromised by practical investment challenges and perceived insufficiencies of current products, notably in the form of insufficient transparency and insufficient information.

Our results confirm earlier research on the need for transparency of index investors in general. In particular, Amenc and Ducoulombier (2014) found a strong conviction among respondents that transparency offered by index providers in general is currently inadequate. Moreover, their results show that the rise of strategy indices makes transparency even more important and that opacity undermines the credibility of reported track records, in particular for new forms of indices. When reviewing existing indices and their disclosure practices, Amenc and Ducoulombier (2014) find that a number of providers failed to disclose the full calculation methodology that would allow for replication of their strategy indices (e.g. formulae or procedures were not properly described or specified, proprietary or third party models were used but not provided). They also find that for smart beta indices used by UCITS, only three out of five index firms provided a full history of their index closing levels. In our survey, we find similar strong evidence on severe shortcomings of alternative equity beta strategies in terms of the transparency they provide to investors. In fact, "limited information on risks" and "limited access to data" appear to be some of the biggest hurdles in terms of alternative equity beta adoption by investors. Moreover, when asked about the importance of different assessment criteria when evaluating advanced beta offerings, respondents saw transparency as one of the key criteria

17 - Respondents were asked to indicate the method they prefer, based on a list of criteria, to gain exposure to alternative risk premia.
18 - Respondents were asked to express their agreement with a list of statements relating to the combination of alternative equity beta strategies.
19 - Respondents were asked which requirements they consider to be important for a factor-tilted alternative equity beta strategy and to indicate if currently available products fulfill each requirement.

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(also refer to items 4 and 5 in the list above).

In addition to finding confirmation in our recent survey of the challenges with transparency and information on alternative equity beta indices, investors' responses to our survey also suggest that they are likely to require more education not only on the benefits but also on the risks of advanced beta investing. In particular, one of the key risks of any advanced beta equity strategy is the relative risk with respect to a cap-weighted reference index. It is often the case that investors maintain the cap-weighted index as a benchmark, which has the merit of macro-consistency and is well-understood by all stakeholders. In this context, advanced equity beta strategies can be regarded as a reliable cost-efficient substitute to expensive active managers, and the most relevant perspective is not an absolute return perspective, but a relative perspective with respect to the cap-weighted index. However, relative risk of advanced beta equity strategies is often not emphasised by providers, and perhaps not enough attention is given to implementing suitable methods to benefit from the outperformance potential of alternative beta strategies while controlling the relative risk with respect to standard cap-weighted benchmarks (also see Amenc *et al.* (2014d)).

Another key conclusion from our survey is that there is a need that investors dedicate sufficient resources to due diligence on the buy-side, that they require access to readily-available strategy and factor combinations, and to more suitable factor investing products.

Overall, we hope that our survey provides food for thought for both investors and product providers, and helps to raise awareness on issues that need to be addressed for advanced beta strategies to reach their full potential.

Introduction

Introduction

Alternative equity beta investing has received increasing attention in the industry recently. Although products in this segment currently represent only a fraction in assets, there has been tremendous growth recently both in terms of assets under management, and – perhaps more strikingly – in terms of new product development. The objective of the research presented in this document is to provide insights into the conceptual background and the current industry practices of alternative equity beta investing.

A definition of the scope of our analysis is in order at this stage. Alternative equity beta refers to systematic, rules-based strategies that do not primarily rely on market cap to select or weight stocks. While we use the term alternative equity beta throughout this document, the concept is also referred to as advanced beta, smart beta, beta plus or beta prime, non-cap-weighted indices or strategy indices. For example, the Financial Times Lexicon states that smart beta refers to "rules-based investment strategies that do not use the conventional market capitalisation weights."[20] This is in line with our definition of alternative equity beta. However, such a definition focuses on a negative determination by defining alternative beta as being different from standard market cap indices. It is clear, however, that any definition of alternative equity beta should also consider positive aspects. On this aspect, it is insightful that Towers Watson (2013) states that smart beta strategies, relative to traditional beta either offer a "wider spread of risk premia than conventional systematic strategies", or access to "risk premium previously only available through expensive active strategies in a cheaper way." In addition to being systematic, alternative beta strategies aim at providing investors with low cost tools. This focus on keeping costs low is important as costs have been shown to be an important determinant of long-term investment performance (see e.g. Fama and French 2010). Moreover, alternative beta products aim to provide beta rather than alpha, implying that returns of alternative beta products can be explained by exposures to rewarded risk factors rather than by "skill" in the form of superior access to or superior analysis of information on security returns. We can summarise our discussion by defining alternative equity beta strategies as systematic, low cost equity investment strategies aimed at capturing risk premia that are different from the broad equity market premium. We include both long-only and long/short equity strategies in our analysis. It should be noted, however, that we focus only on equity markets and do not consider systematic investment strategies that try to extract risk premia from other asset classes such as commodities, currencies, fixed income instruments, etc. (The interested reader is referred to Asness, Frazzini and Pedersen 2012 for an analysis of risk premia within different asset classes).

20 - See <http://lexicon.ft.com/Term?term=smart-beta>

The development of alternative equity beta strategies has to be seen against the backdrop of increasing questioning of the appropriateness of broad cap-weighted equity indices as performance benchmarks. The world's largest pension fund, the California Public Employees' Retirement System (CalPERS) announced in 2006 that it would invest part of its assets to track a fundamentally-weighted index and thus complement its market cap based exposure. The willingness of the fund to improve its returns in an otherwise low-return environment by resorting to a new indexation methodology was

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cited as the main reason for the move.[21] Many institutional investors followed similar moves towards alternative beta indices. However, with increasing product variety in the alternative equity beta space, investors started to combine different methodologies to diversify strategy-specific risks. For example, among sovereign wealth funds, the Korea Investment Corporation (KIC) decided in 2011 to allocate to three different alternative equity beta indices to diversify its developed equity market exposure away from standard cap-weighted benchmarks. In addition to some large initial allocations, many investors have started to review alternative beta strategies without necessarily making a choice on implementation. For example, the Parliament of Norway which acts as a trustee for the Norwegian Oil Fund, commissioned a report on the investment returns of the fund. This report was requested after the fund's performance fell short of the performance of popular equity market benchmarks. The resulting report (Ang, Goetzmann and Schaefer 2009) showed that the returns relative to a cap-weighted benchmark of the actively managed portfolio of the fund can be explained by exposure to a set of well-documented alternative risk factors. After taking into account such exposures, active management did not have any meaningful impact on the risk and return of the portfolio. The authors argue that such exposures can be obtained through purely systematic strategies without a need to rely on active management. Therefore, rather than simply observing the factor tilts brought by active managers ex-post, investors may consider which factors they wish to tilt to and make explicit decisions on these tilts. Thus this discussion of the sources of outperformance of active managers has naturally led to considering factor indices as a more cost-efficient and transparent way of implementing such factor tilts. In a follow up study for the Norway fund (MSCI 2013), index providers analysed how exposures to factors such as value and momentum can be implemented through alternative beta indices. In parallel to the discussions of institutional investors, providers of exchange traded products have rolled out a series of factor-based equity investment products. What all these cases have in common is that investors look beyond standard market cap indices to harvest new sources of outperformance while maintaining many of the benefits of cap-weighted indices notably systematic rules and low cost.

The increasing interest of large institutional investors for alternative equity beta strategies has led providers of exchange traded products to launch a variety of alternative equity beta products that track new forms of indices. It is, however, commonly admitted that the mainstay of smart beta investing is with mandates of sophisticated institutional investors. In that respect, while aggregate market statistics are not readily accessible, it is instructive to note that some put the number of total assets managed in smart beta funds or mandates at 200bn USD as of 2013.[22]

The objective of the present document is to provide insights into the conceptual background and the current industry practices of smart beta equity investing.

21 - ETF.com, 2006, "CalPERS goes Fundamental", available at <http://www.etf.com/sections/news/585.html?iu=1>
22 - This number is cited in http://www.top1000funds.com/analysis/2013/05/29/pushing-smart-beta-further/. The Economist, in July 2013, estimates the assets managed in smart beta funds to be 142 USD bn ("The rise of Smart Beta", The Economist, July 2013).

Introduction

Part I
Conceptual Background: The Forms of Smart and Alternative Beta in the Equity Universe

1. The Emergence of Alternatives to Cap-weighted Indices

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1.1 Criticism of Cap-weighted Indices

Cap-weighted indices have been widely criticised. In fact, cap-weighted equity indices would be truly optimal if the CAPM was true and the indices reflected the true market portfolio. Both these conditions are not verified in practice. Such criticism necessarily leads to investors developing alternatives to cap-weighted indices. Indeed, the criticism of cap-weighted indices is the starting point for smart beta strategies. There are two angles that can be taken and both of these angles correspond to sides of the same coin (the inefficiency of cap-weighted indices):
i) CW indices ignore other priced risk factors. The optimal portfolio should tilt to multiple risk factors based on the investor's preferences.
ii) CW indices are ill diversified portfolios. They are highly concentrated and trend following. The optimal portfolio should allocate weights based on (estimates of) stocks' risk and return parameters rather than by market cap.

The first angle has led to the development of factor strategies (cf. Section 2). The second has led to the development of diversification-based weighting schemes (cf. Section 3).

1.2 Conceptual Clarifications:

1.2.1 Factor vs. Smart Factor

Factor indices fall into two major categories. The first involves selecting stocks that are most exposed to the desired risk factor and the application of a cap-weighting scheme to this selection. While this approach responds to one limitation of cap-weighted indices, namely the choice of exposure to a good factor, the problem of poor diversification arising from high concentration in a small number of stocks remains unanswered. The second method involves maximising the exposure to a factor, either by weighting the whole of the universe on the basis of the exposure to this factor (score/rank weighting), or by selecting and weighting by the exposure score of the stock to that factor. Here again, the maximisation of the factor exposure does not guarantee that the indices are well-diversified.

To overcome these difficulties, index providers that generally offer factor indices on the basis of the first two approaches have recently sought to take advantage of the development of smart beta indices to offer investors a new framework for factor investing (Bender *et al.* (2010)). In fact, index providers have recognised that the traditional factor indices they previously offered are not good investable proxies of the relevant risk factors due to their poor diversification, and that the smart beta indices aiming at improved diversification have implicit risk exposures. As a result, providers are proposing to select and combine indices according to their implicit factor exposures. For example, one could seek exposure to the value factor through a fundamental-weighted index. This however will not produce a well-diversified index, simply because the integration of the attributes characterising the value exposure into the weighting does not take the correlations between these stocks into account. Moreover, the value tilt is an implicit result of the weighting methodology and it is questionable whether an investor seeking a value tilt would wish to hold any weight in growth stocks which will be present in a fundamentally-weighted index. Similarly, seeking exposure to the size factor through equal-weighting of a

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broad universe is certainly less effective than selecting the smallest size stocks in the universe and then diversifying them, including with an equal-weighted weighting scheme. Furthermore, a Minimum Volatility portfolio on a broad universe does not guarantee either the highest exposure to low volatility stocks or the best diversification of this low volatility portfolio. As the examples show, the drawback of this approach is that it maximises neither factor exposure nor diversification of the indices. Such factor indices belonging to the first generation of smart beta products cannot be expected to provide satisfactory control of rewarded risks or diversification of the unrewarded risks. An important challenge in factor index construction is to design well-diversified factor indices that capture rewarded risks while avoiding unrewarded risks. We draw on a second generation of smart beta strategies which allow investors to explore different smart beta index construction methods in order to construct a benchmark that corresponds to their own choice of factor tilt and diversification method. It allows investors to manage the exposure to systematic risk factors and diminish the exposure to unrewarded strategy-specific risks (see Amenc, Goltz and Lodh (2012), and Amenc, Goltz and Martellini (2013)).
Stock selection, the first step in index construction, allows investors to choose the right (rewarded) risk factors to which they want to be exposed. When it is performed upon a particular stock-based characteristic linked to stocks' specific exposure to a common factor, such as size, stock selection allows this specific factor exposure to be shifted, regardless of the weights that will be applied to individual portfolio components.

A well-diversified weighting scheme allows unrewarded or specific risks to be reduced. Stock-specific risk (such as management decisions, product success etc.) is reduced through the use of a suitable diversification strategy. However, due to imperfections in the model there remain residual exposures to unrewarded strategy-specific risks. For example, Minimum Volatility portfolios are often exposed to significant sector biases. Similarly, in spite of all the attention paid to the quality of model selection and the implementation methods for these models, the specific operational risk remains present to a certain extent. For example, robustness of the Maximum Sharpe Ratio scheme depends on a good estimation of the covariance matrix and expected returns. The parameter estimation errors of optimised portfolio strategies are not perfectly correlated and therefore have potential to be diversified away (Kan and Zhou (2007), Amenc *et al.* (2012)). A Diversified Multi-Strategy approach[23], which combines the five different weighting schemes in equal proportions, enables the non-rewarded risks associated with each of the weighting schemes to be diversified away.

The flexible index construction process used in second generation smart beta indices thus allows the full benefits of smart beta to be harnessed, where the stock selection defines exposure to the right (rewarded) risk factors and the smart weighting scheme allows unrewarded risks to be reduced.

23 - Diversified Multi-Strategy weighting is an equal weighted combination of the following five weighting schemes - Maximum Deconcentration Diversified Risk Weighted, Maximum Decorrelation, Efficient Minimum Volatility and Efficient Maximum Sharpe Ratio (see Gonzalez and Thabault (2013)).

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In what follows, we present an example where we illustrate the difference between the beta and smart beta indices using the Long-Term Track Record ERI Scientific Beta indices. We focus on the ERI Scientific Beta Maximum Deconcentration Index which equally weights all its constituents regardless of their market cap. Typically, such a weighting scheme has a stronger size effect than its cap-weight benchmark reference.

The table illustrates the difference between beta (i.e., no stock selection) and smart beta (i.e., with stock selection). The "beta" part corresponds to the choice of the factor tilt which in our case is the size factor and the "smart" part corresponds to the weighting scheme. When we only apply the weighting scheme without any stock selection we only aim to diversify the unrewarded risk factors. However, when we apply both stock selection and weighting scheme we seek to retrieve both the benefits of the diversification and manage the exposure to systematic risk. Both elements work well together and clearly show in the table as we see in panel B that the ERI Scientific Beta Mid-Cap Maximum Deconcentration index has a higher exposure to systematic risk (i.e. the exposure to systematic risk such as SMB and HML is accentuated) which in turn translates into a higher Sharpe ratio of 0.55. Therefore, this illustration makes the case for "smart beta" indices as a better alternative to "beta" indices.

1.2.2 Asset Allocation vs. Risk Allocation

Risk allocation has gained increasing popularity among sophisticated investors, as is perhaps evidenced by the increasing number of papers, too numerous to be cited, recently published on the subject in the practitioner literature, What the concept exactly means, however, arguably deserves some clarification. Indeed,

Table 1: An Illustration of "Beta" and "Smart Beta" Indices – The table shows the performance and risk (in Panel A) and Fama-French factor exposure (in Panel B) of the ERI Scientific Beta Maximum Deconcentration Indices (with no stock selection and mid-cap stock selection). The analysis is based on daily total return data from 1 Jan 1970 to 31 December 2013. The SciBeta USA CW index is used as reference to compute the excess returns and tracking errors.

Scientific Beta USA Long-Term Track Records	Panel A		Scientific Beta USA Long-Term Track Records	Panel B	
	Maximum Deconcentration			Maximum Deconcentration	
	Stock Selection			Stock Selection	
Performance and Risk as of 31 Dec 2013	None	Mid-Cap	Fama-French Analysis as of 31 Dec 2013	None	Mid-Cap
Ann Excess Returns	2.65%	1.10%	Alpha	0.95%	1.74%
Tracking Error	4.25%	2.53%	MKT	1.00	1.01
Sharpe Ratio	0.48	0.55	SMB	0.21	0.36
Volatility	17.41%	18.14%	HML	0.13	0.19
Maximum DD %	58.70%	62.00%	R^2	0.97	0.93

1. The Emergence of Alternatives to Cap-weighted Indices

various interpretations exist for what is sometimes presented as a new investment paradigm and sometimes presented as a simple re-interpretation of standard portfolio construction techniques.

To obtain a better understanding of the true meaning of risk factor allocation, it is useful to go back to the foundations of asset pricing theory. Asset pricing theory suggests that individual securities earn their risk premium through their exposures to rewarded factors (see Merton's (1973) Intertemporal Capital Asset Pricing model for equilibrium arguments or Ross's (1976) Arbitrage Pricing Model for arbitrage arguments). In this context, one can argue that the ultimate goal of portfolio construction techniques is to invest in risky assets so as to ensure efficient diversification of specific and systematic risks within the portfolio. Note that the word "diversification" is used with two different meanings. When the focus is on the diversification of specific risks, "diversification" means *reduction* of specific risk exposures, which are not desirable because not rewarded. On the other hand, when the focus is on the diversification of systematic risks, "diversification" means *efficient allocation* to factors that bear a positive long-term reward, with Modern Portfolio Theory suggesting that efficient allocation is in fact maximum risk-reward allocation (maximum Sharpe ratio in a mean-variance context).

This recognition provides us with a first interpretation for what the r*isk allocation paradigm* might mean. If the whole focus of portfolio construction is ultimately to harvest risk premia to be expected from holding an exposure to rewarded factors, it seems natural to express the allocation decision in terms of such risk factors. In this context, the term "factor allocation" is a new paradigm advocating that investment decisions should usefully be cast in terms of risk factor allocation decisions, as opposed to asset class allocation decisions, which are based on somewhat arbitrary classifications.

The second interpretation for what the risk allocation paradigm might mean is to precisely define it as a portfolio construction technique that can be used to estimate what an efficient allocation to underlying components (which could be asset classes or underlying risk factors), should be. The starting point for this novel approach to portfolio construction is the recognition that a heavily concentrated set of risk exposures can be hidden behind a seemingly well-diversified allocation. In this context, the risk allocation approach, also known as the risk budgeting approach, to portfolio construction, consists in advocating a focus on risk, as opposed to dollar, allocation. In a nutshell, the goal of the risk allocation methodology is to ensure that the contribution of each constituent to the overall risk of the portfolio is equal to a target risk budget (see Roncalli (2013) for a comprehensive treatment of the subject). In the specific case when the allocated risk budget is identical for all constituents of the portfolio, the strategy is known as *Risk Parity*, which stands in contrast to an equally-weighted strategy that would recommend an equal contribution in terms of dollar budgets. To better understand the connection between this portfolio construction technique and standard recommendations from modern portfolio selection techniques, it is useful to recognise that, when applied to uncorrelated factors, risk budgeting is consistent with mean-variance portfolio optimisation under the assumption that

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Sharpe ratios are proportional to risk budgets[24]. Thus, risk parity is a specific case of risk budgeting, a natural neutral starting point that is consistent for uncorrelated factors with Sharpe ratio optimisation assuming constant Sharpe ratios at the factor level.

Such risk allocation techniques, defined as portfolio construction techniques focusing on allocating wealth proportionally to risk budgets, can be used in two different contexts, across asset classes (for the design of a policy portfolio) or within asset classes (for the design of an asset class benchmark). In an asset allocation context, the focus of risk parity is to allocate to a variety of rewarded risk factors impacting the return on various asset classes so as to equalise (in the case of a specific focus on risk parity) the risk contribution to the policy portfolio variance. Within a given asset class, e.g., equities, risk parity can be applied to portfolio returns in the rare instances when there is no pre-existing benchmark, or, more often than not, to portfolio *relative* returns with respect to the investor's existing benchmark. In the latter case, it is typically the contribution of risk factors impacting the returns on the asset class (e.g., the Fama-French factors for equities) to portfolio tracking error that matters, and not variance. Hence, just as minimising variance is the appropriate objective when the focus is on risk minimisation in an absolute context while minimising *tracking error* is the appropriate objective when the focus is on risk minimisation in a relative context, equalising contributions to risk can also apply in an absolute risk context or in a relative risk context.

Overall, it appears that risk allocation can be thought of *both* as a new investment paradigm advocating a focus on allocating to uncorrelated rewarded risk factors, as opposed to correlated asset classes, and a portfolio construction technique stipulating how to optimally allocate to these risk factors. It should be noted in closing that the existence of uncorrelated long/short factor-replicating portfolios is not a necessary condition to perform risk budgeting, which is fortunate since such uncorrelated pure factors are hardly investable in practice. Indeed, one can use any set of well-diversified portfolios, as opposed to factor-replicating portfolios, as constituents, leaving to the asset allocation stage the hurdle to reach target factor exposures. For example, Amenc, Deguest and Martellini (2013) use long-only factor-tilted smart beta benchmarks as constituents and choose the allocation to these constituents so as to ensure that the contributions of standard rewarded equity factors to the tracking error of the portfolio with respect to the cap-weighted benchmark are all equal.

It is in a framework of this kind that the research conducted by EDHEC-Risk Institute to define the concept of smart factor risk allocation is situated. It involves offering both the ingredients and the allocation methods that allow one to benefit on the one hand from the diversification offered by smart beta weighting schemes, which reduce the unrewarded or specific risks, and on the other to make an efficient allocation to systematic or rewarded risk factors. This dual perspective is an effective response to the traditional criticism of cap-weighted indices, which are both poorly-diversified, because they are highly concentrated in a small number of large cap stocks, and exposed to poorly rewarded risk factors such as Large and Growth stocks.

24 - Orthogonalising the factors is useful to avoid the arbitrary attribution of overlapping correlated components in the definition of risk budgets allocated to each of these factors. Principal component analysis (PCA) can be used to extract uncorrelated versions of the factors starting from correlated asset or factor returns (see for example Roncalli and Weisang (2012) or Deguest, Martellini and Meucci (2013)).

1. The Emergence of Alternatives to Cap-weighted Indices

In the coming section, we thoroughly describe the standard risk factors in the equity universe.

1. The Emergence of Alternatives to Cap-weighted Indices

2. Equity Risk Factors and Factor Indices

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Asset pricing theory postulates that multiple sources of systematic risk are priced in securities markets. In particular, both equilibrium models such as Merton's (1973) Intertemporal Capital Asset Pricing Model and arbitrage models such as Ross's (1976) Arbitrage Pricing Theory allow for the existence of multiple priced risk factors. The economic intuition for the existence of a reward for a given risk factor is that exposure to such a factor is undesirable for the average investor because it leads to losses in bad times[25] (i.e. when marginal utility is high, see e.g. Cochrane 2000). This can be illustrated for example with liquidity risk. While investors may gain a payoff from exposure to illiquid securities as opposed to their more liquid counterparts, such illiquidity may lead to losses in times when liquidity dries up and a flight to quality occurs, such as during the 1998 Russian default crisis and the 2008 financial crisis. In such conditions, hard-to-sell (illiquid securities) may post heavy losses.

While asset pricing theory provides a sound rationale for the existence of multiple factors, theory provides little guidance on which factors should be expected to be rewarded. Empirical research however has come up with a range of factors that have led to significant risk premia in typical samples of data from US and international equity markets[26]. A key requirement for investors to accept factors as relevant in their investment process is however related to the presence of a clear economic intuition as to why the exposure to this factor constitutes a systematic risk that requires a reward and is likely to continue producing a positive risk premium (see Ang (2014) and Cochrane (2000)).

Harvey, Liu and Zhu (2014) review the empirical literature that has identified factors that impact the cross section of expected stock returns and count a total

Table 2a: Examples of Equity Risk Factors and their classification according to the risk factor taxonomy of Harvey, Liu and Zhu (2014).

	Common Risk Factors (Systematic)	Individual Risk Factors (Characteristics)
Financial	Market factor (Sharpe 1964)	Idiosyncratic volatility (Ang *et al.* 2006)
Macro	Consumption growth (Breeden 1979)	N.A.
Microstructure	Market Liquidity (Pastor and Stambaugh 2003)	Short sale restrictions (Jarrow 1980)
Behavioural	Investor sentiment (Baker and Wurgler 2006)	Analyst Dispersion (Diether, Malloy and Scherbina 2002)
Accounting	Book-to-market portfolios (Fama and French 1992)	Price-earnings ratio (Basu 1977)
Other	Momentum portfolio (Carhart 1997)	Political campaign contributions (Cooper, Gulen and Ovtchinnikov 2010)

Table 2b: Examples of factor risk premium reported in the literature

Historical factor premiums over the 1926-2008 period	Average premium	T-statistic
Equity market premium	7.72%	3.47
Small-Cap premium	2.28%	1.62
Value premium	6.87%	3.27
Momentum premium	9.34%	5.71

Sources: Ang et al. (2009), Koedijk, Slager and Stork (2013)

25 - It is worth emphasising that asset pricing theory suggests that factors are (positively) rewarded if and only if they perform poorly during bad times, and more than compensate during good times so as to generate a positive excess return on average across all possible market conditions. In technical jargon, the expected excess return on a factor is proportional to the negative of the factor covariance with the pricing kernel, given by marginal utility of consumption for a representative agent. Hence, if a factor generates an uncertain payoff that is uncorrelated to the pricing kernel, then the factor will earn no reward even though there is uncertainty involved in holding the payoff. On the other hand, if a factor payoff co-varies positively with the pricing kernel, it means that it tends to be high when marginal utility is high, that is when economic agents are relatively poor. Because it serves as a hedge by providing income during bad times, when marginal utility of consumption is high, investors are actually willing to pay a premium for holding this payoff.

26 - These effects are often referred to as "*anomalies*" in the academic literature as they contradict the CAPM prediction that the cross section of expected returns only depends on stocks' market betas and should be void of any other patterns. However, when using a more general theoretical framework such as the intertemporal CAPM or Arbitrage Pricing Theory, there is no reason to qualify such patterns as anomalies.

2. Equity Risk Factors and Factor Indices

of 314 factors for which results have been published. They provide a taxonomy of these factors which we summarise in table 2.a.

We report in table 2.b examples of factor premium reported in the literature with their t-stat. We observe that the small-cap premium is not statistically significant over the long term.

Before turning to a detailed discussion for each risk factor we will provide an overview of factors used in common multi-factor models of expected returns following the seminal work of Fama and French (1993) and Carhart (1997) and recent empirical evidence (Hou, Karolyi and Kho (2011), Fama and French (2012, 2014)). Fama and French have carried out several empirical studies to identify the fundamental factors that explain average asset returns, as a complement to the market beta. They highlighted two important factors that characterise a company's risk: the book-to-market ratio and the company's size measured by its market capitalisation. Fama and French therefore propose a three-factor model[27], which is formulated as follows:

$$E(R_{i,t}) - R_F = b_{1,i} * (E(R_{M,t}) - R_F) + b_{2,i} * E(SMB_t) + b_{3,i} * E(HML_t) \quad (1)$$

Where $E(R_{i,t})$ denotes the expected return of asset i; R_F denotes the rate of return of the risk-free asset; $E(R_{M,t})$ denotes the expected return of the market portfolio; $E(SMB_t)$ (small-minus-big) denotes the difference between returns on two portfolios: a small-capitalisation portfolio and a large capitalisation portfolio; $E(HML_t)$ (high-minus-low) denotes the difference between returns on two portfolios: a portfolio with a high book-to-market ratio and a portfolio with a low book-to-market ratio;

$b_{k,i}$ denotes the factor loadings. The $b_{k,i}$ are calculated by regression from the following equation:

$$R_{i,t} - R_F = \alpha_i + b_{1,i} * (R_{M,t} - R_F) + b_{2,i} * SMB_t + b_{3,i} * HML_t + \varepsilon_i \quad (2)$$

Fama and French (1996) analysed a range of cross-sectional return patterns such as the higher returns associated with contrarian stocks, stocks with low past sales growth, stocks with low price-earnings ratios and low debt to equity ratios. They conclude that their three-factor model appropriately captures such effects. Therefore, the three-factor model can be seen as a parsimonious way of capturing a range of seemingly different return patterns that have been highlighted in the empirical literature. However, the three-factor model is not able to capture high returns to past short-term winner stocks. Carhart (1997) extended Fama and French's three-factor model where the additional factor is momentum, which enables the persistence of the returns to be measured. This factor was added to take the anomaly revealed by Jegadeesh and Titman (1993) into account. With the same notation as above, this model is written:

$$E(R_{i,t}) - R_F = b_{1,i} * (E(R_{M,t}) - R_F) + b_{2,i} * E(SMB_t) + b_{3,i} * E(HML_t) + b_{4,i} * E(PR1YR_t) \quad (3)$$

where PR1YR denotes the difference between the average of the highest returns and the average of the lowest returns from the previous year. Fama and French (2012) analyse how the four-factor model of Carhart (1997) performs in explaining

27 - Cf. Fama and french (1993).

2. Equity Risk Factors and Factor Indices

the cross section of stock returns in developed equity markets around the world. They analyse stocks for four regions (North America, Europe, Japan and Asia Pacific excluding Japan). They find that both the value and the momentum effect are more pronounced in small-cap stocks, and especially micro-cap stocks, than in large cap stocks. In particular, neither the large cap momentum factor nor the large cap value factor have returns that are significantly different from zero at conventional levels of significance, and the difference of factor returns within small-cap stocks compared to within large cap stocks is significant for both the value and momentum factor. Moreover, they show that in order to explain return differences across equity portfolios within each of the four regions, local factors perform better than global factors, implying that factor pricing is not integrated across regions. Hou, Karolyi and Kho (2011) compared the explanation power of traditional factor models such as the CAPM or models using size and book-to-market factors with a factor model including a value-based factor based on cash flow-to-price instead of book-to-market. Using monthly returns for over 27,000 stocks from 49 countries over the period from 1981 to 2003, they found that pricing errors for the latter model is lower than for traditional models and leads to fewer model rejections. In addition, they found that including an additional factor based on stock price momentum usefully complements the explanatory power of the cash flow-to-price factor. Fama and French (2014) propose a five-factor model that includes two additional factors (namely the profitability and investment factors) to the initial factors (market, size and B/M) of their three-factor model (Fama and French, 1993). The authors find that the model provides an acceptable description of average returns on portfolios formed on size and one or two of B/M, operating profitability, and investment.

Investors who can identify rewarded risk factors and are able to accept to bear the corresponding systematic risk exposures have also to come up with practical ways of implementing the exposure to such factors. Therefore, implementation issues are of crucial importance. In particular, since most factors require frequent adjustments of positions, transaction costs and tax effects may create a gap between the empirical evidence on factor portfolios and the payoffs attainable in practice. The first subsection below reviews the empirical evidence for a range of widely documented risk factors, explains the standard design of factor portfolios and potential refinements, and reviews the economic explanation for the existence of the corresponding factor premium. A second subsection then turns to a discussion of several implementation issues that arise across different factors, such as the use of long and short positions and the impact of transaction costs. A third subsection provides an overview of equity factor indices available from major index providers.

2.1 Review of Common Equity Risk Factors

This section will review the most widely used and most thoroughly documented equity risk factors. We will explain both the standard construction approach for each risk factor, existing improvements for constructing factor portfolios, as well as the economic rationale for the existence of a reward for each respective risk factor. Before commencing the detailed discussion for each of these factors, we provide a short overview as an introduction.

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While asset pricing theory provides a sound rationale for the existence of multiple factors, theory provides little guidance on which factors should be expected to be rewarded. Empirical research however has come up with a range of factors that have led to significant risk premia in typical samples of data from US and international equity markets[28]. A key requirement of investors to accept factors as relevant in their investment process is however that there is a clear economic intuition as to why the exposure to this factor constitutes a systematic risk that requires a reward and is likely to continue producing a positive risk premium (see Ang (2014), also compare Cochrane (2000) who refers to the practice of identifying merely empirical factors as "factor fishing").

Harvey, Liu and Zhu (2014) review the empirical literature that has identified factors that impact the cross section of expected stock returns and count a total of 314 factors for which results have been published. Table 3 provides an overview of the main factors used in common multi-factor models of expected returns and the references to seminal work providing empirical evidence. It is interesting to note that these factors have been found to explain expected returns across stocks not only in US markets, but also in international equity markets, and – in many cases – even in other asset classes including fixed income, currencies and commodities.

28 - These effects are often referred to as "anomalies" in the academic literature as they contradict the CAPM prediction that the cross section of expected returns only depends on stocks' market betas and should be void of any other patterns. However, when using a more general theoretical framework such as the intertemporal CAPM or Arbitrage Pricing Theory, there is no reason to qualify such patterns as anomalies.

Table 3: Empirical Evidence for Selected Factor Premia: Key References

	Factor Definition	Within US Equities	International Equities	Other Asset Classes
Value	Stocks with high book-to-market versus stocks with low book-to-market	Basu (1977) Rosenberg, Reid, Lahnstein (1985) Fama and French (1993)	Fama and French (2012)	Asness, Moskowitz, Pedersen (2013)
Momentum	Stocks with high returns over the past 12 months omitting the last month versus stocks with low returns	Jegadeesh and Titman (1993), Carhart (1997)	Rouwenhorst (1998)	Asness, Moskowitz, Pedersen (2013)
Low Risk	Stocks with low risk (beta, volatility or idiosyncratic volatility) versus stocks with high risk	Ang, Hodrick, Xing, Zhang (2006), Frazzini and Pedersen (2014)	Ang, Hodrick, Xing, Zhang (2009), Frazzini and Pedersen (2014)	Frazzini and Pedersen (2014)
Size	Stocks with low market cap versus stocks with high market cap	Banz (1981) Fama and French (1993)	Heston, Wessels, Rouwenhorst (1999) Fama and French (2012)	N.A.
Liquidity	Stocks with low trading volume or high sensitivity to changes in market liquidity	Pastor and Stambaugh (2003), Acharya and Pedersen (2005)	Lee (2011)	Lin, Wang, Wu (2011), Sadka (2010)
Profitability	Stocks of firms with high profitability (e.g. return on equity) have high returns	Novy-Marx (2013), Hou, Xue and Zhang (2014), Fama and French (2014)	Ammann, Odoni, Oesch (2012)	N.A.
Investment	Stocks of firms with low investment (e.g. change in book value) have high returns	Cooper, Gulen, and Schill (2008) Hou, Xue and Zhang (2014), Fama and French (2014)	Ammann, Odoni, Oesch (2012) Watanabe, Xu, Yao, Yu (2013)	N.A.

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It is worth noting that the debate about the existence of positive premia for these factors is far from closed. Therefore, what is important in addition to an empirical assessment of factor premia is to check whether there is any compelling economic rationale as to why the premium would persist. Such persistence can be expected notably if the premium is related to risk taking. In an efficient market with rational investors, systematic differences in expected returns should be due to differences in risk. Kogan and Tian (2012) argue that to determine meaningful factors "we should place less weight on the [data] the models are able to match, and instead closely scrutinise the theoretical plausibility and empirical evidence in favour or against their main economic mechanisms". This point is best illustrated by the example of the equity risk premium. Given the wide fluctuation of equity returns, the equity risk premium can be statistically indistinguishable from zero even for relatively long sample periods. However, one may reasonably expect that stocks have higher reward than bonds because investors are reluctant to hold too much equity due to its risks. For other equity risk factors, such as value, momentum, low risk and size, similar explanations that interpret the factor premia as compensation for risk have been put forth in the literature. It is worth noting that the existence of the factor premia could also be explained by investors making systematic errors due to behavioural biases such as overreaction or under-reaction to news on a stock. However, whether such behavioural biases can persistently affect asset prices in the presence of some smart investors who do not suffer from these biases is a point of contention. For behavioural explanations to be relevant, it is necessary to assume that – in addition to biases – there are so-called "limits to arbitrage", i.e. some market characteristics that prevent smart investors fully exploiting and the resulting return patterns and thus making them disappear. Therefore, explanations

Table 4. Economic Explanations for Selected Factor Premia: Overview

	Risk-based Explanation	Behavioural Explanation
Value	Costly reversibility of assets in place leads to high sensitivity to economic shocks in bad times	Overreaction to bad news and extrapolation of the recent past leads to subsequent return reversal
Momentum	High expected growth firms are more sensitive to shocks to expected growth	Investor overconfidence and self-attribution bias leads to returns continuation in the short term
Low Risk	Liquidity constrained investors hold leveraged positions in low-risk assets which they may have to sell in bad times when liquidity constraints become binding	Disagreement of investors about high-risk stocks leads to overpricing in the presence of short sales constraints
Size	Low profitability leads to high distress risk and downside risk. Low liquidity and high cost of investment needs to be compensated by higher returns	Limited investor attention to smaller-cap stocks
Liquidity	Assets with low returns in times of funding liquidity constraints or low market liquidity require a risk premium	N.A.
Profitability	Firms facing high cost of capital will focus on the most profitable projects for investments	Investors do not distinguish sufficiently between growth with high expected profitability and growth with low profitability, leading to under-pricing of profitable growth firms
Investment	Low investment reflects firms limited scope for projects given high cost of capital	Investors under-price low investment firms due to expectation errors

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of factor premia as compensation for risk are likely to provide the more compelling case for investment applications. The table below summarises the main economic explanations for common factor premia.

2.1.1 The Size Factor

2.1.1.1 Seminal Papers and Review of the Empirical Evidence

Banz (1981) finds that stocks with lower market capitalisation (small stocks) tend to have higher average returns. This finding has been confirmed by Roll (1983) and Fama and French (1992) who show that small stocks on average outperform large stocks (based on market capitalisation) even after adjusting for market exposure (Israel and Moskowitz, 2013). Since the publication of Banz's 1981 paper, other studies have investigated the explanation of the size effect in the US universe. Van Dijk (2011) presents a review of them. Reinganum (1981) uses a sample of 566 NYSE and Amex firms over the period 1963-1977 and finds that the smallest size decile outperforms the largest by 1.77% per month. Brown et al. (1983), using the same data sample as Reinganum, constructed 10 size-based portfolios and find the existence of a quasi linear relation between the average daily return of the portfolios and the logarithm of their average market capitalisation. Keim (1983), using a sample of NYSE and AMEX stocks larger than Reinganum (1981), over the period from 1963 to 1979, identifies a size premium of at least 2.5% per month. Lamoureux and Sanger (1989) find a size premium of 2.0% per month for Nasdaq stocks and of 1.7% for NYSE/Amex stocks over the period 1973–1985. Finally, Fama and French (1992), using a sample of NYSE, Amex, and Nasdaq stocks over a larger period than previous studies (1963-1990), find that the smallest size decile outperforms the largest by 0.63% per month.

As far as the international evidence on the size effect is concerned, the evidence of the presence of such effect is also large. In what follows we list some of the studies that investigated this anomaly using non-US data: Australia: Beedles (1992), Canada: Elfakhani *et al.* (1998), China: Drew *et al.* (2003), Emerging markets: Rouwenhorst (1999), Europe: Annaert *et al.* (2002), Japan: Chan *et al.* (1991), Korea: Kim *et al.* (1992), Turkey: Aksu and Onder (2003), United Kingdom: Bagella *et al.* (2000).

At first sight, the presence of the size effect seems to be consistent across different universes. However, a closer inspection of the recent and "not-so-recent" literature show that the empirical robustness of such effect is quite fragile. In the next section, we briefly review the literature to justify such a statement.

2.1.1.2 Controversy Around the Robustness of the Size Effect

Several studies argue that the size effect identified empirically in stocks returns is the result of data mining, missing data, the inclusion of extreme observations in the sample, or even due to the existence of seasonal effects. Van Dijk (2011) presents a review on the subject of robustness of size effect over time. Banz (1981) and Keim (1983) both investigate the 1926-1975 period in the US and observe great variations in the size effect. Also in US, Handa et al. (1989) compare the result obtained on the whole 1941-1982 period, with the ones obtained using three sub-periods, and they observe large differences in the size effect. Pettengill et al. (2002) investigate the case of different market conditions and find differences in the size effect regardless of whether in bull or bear markets.

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Another issue concerns the persistence of the size effect over time. Van Dijk (2011) reviews several authors that have investigated time periods beginning in the 1980s. Those papers do not identify size premium, leading to the conclusion that the size effect does not persist after the early 1980s. Among them, Eleswarapu and Reinganum (1993) over the 1980-1990 period, Dichev (1998) over the 1980–1995 period, Chan et al. (2000) over the 1984-1998 period, Horowitz et al. (2000a, 2000b) over the 1979-1995 and the 1982-1996 periods, and Amihud (2002) over the 1980-1997 period. In the same way, Hirshleifer (2001) reports a disappearance of the size effect after 1983. Other authors report a reverse size effect since the 1980s, namely Dimson and Marsh (1999), who measure a performance for large stocks of 2.4% higher than that of small stocks over the 1983-1997 period. Finally, Schwert (2003) argues that the disappearance of the size effect anomaly happens in the same time practitioners discovered it and began to develop investment strategies based on it.

Van Dijk (2011) notes that the reason why a decline in the size premium in the US after the early 1980s was observed is not clearly explained. According to Elton (1999), it could be a temporary phenomenon, explained by the deviation of realised returns from expected returns in the 1980s and 1990s, due to information surprises, both for small and large stocks. In the same way, Hou and Dijk (2014) argue that the size effect still exists. They also explain the disappearance of the size effect after the early 1980s as a consequence of realised returns differing from expected returns due to small firms experiencing large negative profitability shocks during this period, while big firms were experiencing large positive shocks. They develop a model allowing them to adjust the results for the price impact of these profitability shocks and conclude that a robust size effect still exists in the cross section of expected returns. Moreover, De Oliveira Souza (2014) analyses the size premium over a long-term period of 85 years and finds that the premium is positive most of the time, and statistically significant especially during time periods when risk premia are high (periods with high book-to-market equity of the aggregate stock market).

The controversy around the robustness of the size effect has led the recent literature to focus on the relation between the size effect and other factors (i.e. momentum, value, etc.) as a way to better understand the size anomaly. In the coming section, we mention a few papers that studied such relation rigorously.

2.1.1.3 Relation Between Size and Others Factors

Fama and French (2008) study the relation between the size effect and the other return anomalies (i.e. net stock issues, accruals, book-to-market, momentum, profitability and asset growth). They separately consider three size groups – microcap stocks, small stocks and big stocks – because, given that microcap stocks tend to have more extreme returns, than small or big stocks, a result obtained on all stocks could be dominated by the sole effect generated by microcap stocks. Their results show that the size effect is mainly existent in microcap stocks, but remains marginal among small and big stocks. Note that it is common to refer to stocks which rank highly in terms of market cap either as large cap stocks, large stocks or big stocks, with "big" being used in the study of Fama and French (1993) which labels the size factor as "small-

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minus-big". Here, we use these different terms interchangeably. On the contrary, if the relation between momentum and average returns is strong in all size groups, the highest relation is observed for small and big stocks, while the relation is only about half as strong in the microcap size group. In what concerns relation between average returns and asset growth, we observe a strong negative relation for microcap stocks, a weaker but statistically significant relation for small stocks. However, the relation appears to be non-existent for big stocks. Finally, for all other factors, namely the book-to-market ratio, net stock issues, accruals, and profitability, the average regression slopes are similar for all size groups. Fama and French (2012 examine the value, size and momentum effects in international stocks. The authors find no empirical evidence of size effect in any of the regions[29] studied during their sample period (i.e. from November 1989 to March 2011). However, they find some interesting evidence on how value and momentum returns vary with firm size. They show that (1) small stocks exhibit larger value premiums in all countries, except Japan, (2) the winner-minus-loser spreads in momentum returns is lower for big stocks than for small stocks, and (3) the momentum factor appears to not be significant in Japan, whatever the size group considered.

29 - The authors focus on 23 countries which are USA, Canada, Japan, Australia, New Zealand, Hong Kong, Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom and Singapore.

Finally, Israel and Moskowitz (2013) examine the role that the firm size plays in the efficacy of the investment styles (i.e. value and momentum). Using data over the last 83 years in the U.S. stock market (from 1926 to 2009) and looking across different sized firms, the authors find the existence of a stable momentum premium in all size groups, but little evidence that this premium is stronger for small-cap stocks. In contrast to Fama and French (2012), Israel and Moskowitz (2013) show that momentum returns are similar across size groups. Additionally, they show that the short side is no more profitable than the long side. On the contrary, in what concerns the value premium, there are differences among size groups. The authors identify a significant premium among small stocks, while this premium is not significant among the top 40% of large cap NYSE stocks.

The question why small firms earn higher returns than traditional asset pricing models predict has become the subject of a heated debate. In the coming section, we provide a snapshot of the literature that provides potential explanations to the size effect on equity returns.

2.1.1.4 Economic Rationale for Reward of the Size Effect

Some papers contend that the systematic risk of a stock is driven by multiple risk factors, and firm size is a proxy for the exposure to state variables that describe time variation in the investment opportunity set. Other alternative interpretations are that the size premium is related to investor behaviour and/or extreme returns.

Van Dijk (2011) presents a review of papers. Fama and French (1993) construct portfolios replicating size (SMB) and book-to-market (HML) risk factors. They also form 25 stock portfolios based on size and book-to-market and use the excess returns of these 25 portfolios over the period 1963-1991 as dependent variables. They find that the market, SMB and HML portfolios capture a large part of the return variations on these 25 stock portfolios and conclude that size and book-to market are good proxies to

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common risk factors that stocks returns are sensible to. Chan et al. (1985) show that the size effect in Fama-MacBeth regressions is caught by variables such as the default spread, as well as other variables that capture changes in the economic environment. According to Chan and Chen (1991), small firms are generally "fallen angels" that have lost market value after having encountered bad performance. Vassalou and Xing (2004) investigate the relation between the size and book-to-market effects and default risk. They evidence that the size effect is statistically significant only within the highest default risk quintile. Petkova (2006) finds a link between the size factor and innovations in variables, such as the default spread, and more generally innovations in variables describing investment opportunities. Hwang et al. (2010) propose an extended version of the CAPM including a credit spread factor, this additional factor being interpreted as a proxy for the option feature of equity. They show that this model can explain the size and value effects. Other studies question the conclusion that the size effect can be explained by a risk-based story and suggest a behavioural explanation instead. Gompers and Metrick (2001) explain the decline in the relative performance of small stocks over the 1980–1996 period by the fact that institutional investors tend to hold a growing share of the US equity market, causing more demand for large cap stocks compared to small stocks. This argument can explain the conclusion of Daniel and Titman (1997) that size and book-to-market determine expected returns as characteristics rather than as proxies for risk. Lakonishok et al. (1992) explain that portfolio selection by professional money managers are determined by agency relations, as it is more difficult to justify investments in small stocks to sponsors.

Van Dijk (2011) also notes that the size effect can also originate from incomplete information about small firms, as evidenced by some studies. For example, Merton (1987) predicts higher expected returns for stocks with fewer investors, as they are issued from less well-known firms. Hou and Moskowitz (2005) make an empirical analysis of the link between size effect and the recognition of the firm by investors. They use the average delay with which a firm's stock price reacts to information as a broad measure for market frictions. They find that the price delay has a significant impact on the cross section of US stock returns over the period 1963-2001, and that it captures a substantial part of the size effect. According to them, there is consistency between frictions and investor firm recognition.

Finally, some authors link the size effect to extreme returns. According to Knez and Ready (1997), the size effect is due to the only 1% of extreme values of the data sample. Fama and French (2007) evidence that the size premium is the result of small stocks earning extreme positive returns and becoming bigger stocks.

To conclude, the size effect has been evidenced both in the US and on international equity markets and several economic explanations have been proposed. However, considerable variations in the magnitude of this effect have been observed depending on time periods.

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2.1.2 The Value Factor

2.1.2.1 Seminal Papers and Review of the Empirical Evidence

Value investments favour stocks that have a low price relative to fundamental firm characteristics. While there is a wide range of valuation metrics that are based on a variety of firm characteristics, a valuation measure typically reflects the inverse of scaled price and thus indicates a stock's cheapness. There is ample empirical evidence that – even when controlling for market beta - returns across stocks are positively related to cheapness. In particular, empirical evidence has shown that stock returns tend to increase with variables such as the earnings-to-price ratio (Basu 1977), the book-to-market ratio (Rosenberg, Reid and Lahnstein 1985), the cash flow-to-price ratio (Chan, Hamao and Lakonishok 1991) or more recently pay-out yields (Boudouk *et al.* 2007) as the value premium has been observed not only in US equity markets but also in international equity returns (see for example Chan, Hamao and Lakonishok, 1991; Fama and French, 1998; Rouwenhorst, 1998; Griffin, Ji and Martin, 2003; Asness, Moskowitz and Pedersen, 2013; Chui, Titman and Wei, 2010). In addition, researchers have examined strategies that use other measures that essentially select stocks with low price. For

Table 5: The table shows some examples of new construction methodologies of the value-tilted portfolios taken from recent literature (e.g. Asness and Frazzini (2013), Novy-Marx (2013) and Novy-Marx (2011)).

Authors	Improvements	Results
Asness and Frazzini (2013)	The standard HML factor, on 30 June, uses lagged fiscal year-end prices (31 December) to compute the B/P ratio- this is done in order to match the book values that are only available at minimum of 6 months lag. The authors show that using more current prices is superior to the standard method of using prices at fiscal year-end as a proxy for the true B/P ratio (i.e. ratio as of 30 June). The authors specify that "current" refers only to price at time of portfolio formation, not to book value, which is always lagged.	The authors show that the best measure that proxies for the true, unobtainable and more timely B/P (at June 30) is the measure that incorporates more current prices in the B/P ratio, because as opposed to the standard B/P, the more timely B/P measure does not miss important information. Secondly, the authors show that value portfolios constructed using more current prices earn higher abnormal returns when combined with momentum and other factors. The reason is because failing to update prices when computing B/P is not only an inferior measure of true unobservable B/P, but also reduces the natural negative correlation of value and momentum.
Novy-Marx (2013)	The authors suggest to sort stocks on average of value (B/M) and gross profitability (defined as the product of gross margins[30] and asset turnover[31]) instead of sorting them on value only. The ranking consists of averaging gross profitability and book-to-price ranks. The sorting based on value and quality yields better abnormal returns than value only because gross profitability has more power predicting differences in expected returns across stocks.	The authors show that strategies based jointly on valuation (i.e. value factor) and gross profitability (i.e. quality factor) outperform joint value and quality strategies constructed using other quality metrics (e.g. years of positive earnings, dividend record, earnings per share and enterprise size).
Novy-Marx (2011)	The author shows that the HML factor proposed by Fama-French is not mean-variance efficient and has a priced component (that is related to variation in firm's efficiencies identifiable as differences in book-to-market ratio within industries) and un-priced component (related to industry variation which affects book-to-market (BM) ratios but is largely unrelated to differences in expected returns). The author proposes two alternative measures for constructing value factors that are much closer to the efficient frontier. (1) Sort stocks on the basis of industry relative BM ratio (i.e. the ratio of the BM of firm "j" in industry "i" and the BM of industry "i" or (2) Sort stocks on the basis of intra-industry BM ratio[32].	The industry relative factor has a Sharpe ratio that is twice that of the standard HML factor due to both its higher return and lower standard deviation. Furthermore, the Sharpe ratio of the intra-industry value factor is again twice that of the standard HML factor. The high Sharpe ratio here is driven exclusively by the low volatility of the strategy.

30 - Gross margin is the gross profits to sales.
31 - Asset turnover is the dollar value of annual sales generated by each dollar of book assets.
32 - Intra-industry book to market ratio consists of going long a dollar of inefficient firms (i.e. intra-industry value stocks), short a dollar of efficient firms (i.e. intra-industry growth stocks), short 50 cents of value industries and long 50 cents of growth industries.

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example, DeBondt and Thaler (1985) have shown that stocks with low past returns tend to have higher returns and Lakonishok, Shleifer and Vishny (1994) show that stocks with low growth of sales tend to have high returns. Fama and French (1996) argue that the book-to-market and small-cap factor do a good job at explaining the returns on variants of value portfolios that aim at favouring stocks with low price. Therefore, while recognising that many variants of Value strategies exist, the remainder of the discussion focuses on the most widely used value factor which is based on book-to-market ratios.

2.1.2.2 Constructing Value Factor Portfolios and Improvements to the Basic Value Factor

Asness and Frazzini (2013) present various constructions of HML factors. This factor was introduced by Fama and French (1992, 1993) who use book-to-price (B/P) as the proxy for the value and forms a portfolio that is long high B/P firms and short low B/P firms. Fama and French update their portfolios once a year on 30 June, using book and price for each stock as of the prior 31 December. As a result, the book and price data used to form B/P and value portfolios is always between 6 and 18 months old.

Table 5 presents some recent examples of methods which improve upon the standard construction methodology of the value factor.

As shown in table 5, the value factor has received a substantial attention in the literature and the table only gives a brief overview of such developments. In what follows, we discuss the economic intuition presented so far on what drives the value premium.

2.1.2.3 Economic Rationale for the Value Factor

The value premium is the well-established finding that stocks with high book-to-market ratios (value stocks) yield higher average returns than those with low book-to-market ratios (growth stocks).

Although the definition of the value factor is straightforward, there is still a fierce debate as to what drives this value premium and various explanations have been provided in the literature. A number of papers argue that value firms have time-varying betas which explain their excess returns. In fact, various authors argue that value stocks become more risky in bad times, thus requiring a premium to compensate investors for this risk. Zhang (2005) proposes a model which is based on distinguishing between firms mainly consisting of physical assets in place and firms mainly consisting of growth options. He shows that in bad times when the price of risk is high, assets in place are riskier than growth options. The explanation of these results relies on two salient features of Zhang's model, costly reversibility[33] and countercyclical price of risk. According to Zhang (2005), value firms have to deal with more unproductive capital than growth firms during bad times, making it more difficult for them to reduce their capital stocks. As a result, value firms are riskier than growth firms during these periods of high price of risk, with a high dispersion of risk between value and growth strategies. On the contrary, a low or even negative dispersion of risk between value and growth strategies is observed in good times, during which growth firms invest more and have to face higher adjustment costs to take advantage of favourable economic conditions.

33 - Costly reversibility implies that firms face higher costs in cutting than in expanding capital.

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These findings are consistent with those of Lettau and Ludvigson (2001) and Petkova and Zhang (2003). The findings of Zhang (2005) are also in line with those of Cooper (2006), who argues that firms with a high book-to-market ratio can benefit more from positive shocks than low book-to-market firms in the real economy because they have excess capital. Indeed, as capital investment is largely irreversible, a value firm's excess installed capital capacity allows it to benefit from a positive aggregate shock without undertaking any costly investment. In contrast, a low book-to-market firm would have to undertake costly investment in order to fully benefit from the positive shock.[34]

More recently, Choi (2013) investigates how the interaction between asset risk and financial leverage explain differences between value and growth stocks risk according to economic conditions. The author notes that in a context of unfavourable economic conditions, we observe a large increase in value firm equity betas, as the asset risk and leverage of those firms increase. On the contrary, growth firms' equity betas remain stable over time, as those firms have a low leverage and asset betas that are less sensitive to economic conditions. These arguments explain that value stocks exhibit high risk during bad economic conditions, together with a high risk premium. While most of the previously discussed papers relate the value premium to firm characteristics, another part of the literature discusses the strong link between the value premium and macro risk. For instance, Liew and Vassalou (2000), using data from ten countries, evidence a positive link between the value premium and future GDP growth. As a result, stocks with high book-to-market ratios will benefit more from forthcoming growth in activity than stocks with low book-to-market ratios. Furthermore, Vassalou (2003) finds that news related to future GDP growth is a factor that usefully completes the market portfolio factor in explaining the cross section of returns. In addition, she shows that the HML and SMB Fama-French factors may serve as proxies for news about future GDP growth. Other arguments were proposed in the literature. Fama and French (1993, 1996) suggest that book-to-market is a proxy for a state variable associated with relative financial distress. As value stocks are typically distress stocks, they will do very badly in the event of a credit crunch. Hence, they are risky stocks.

The value effect has been evidenced both in the US and on international markets. It has also been tested on the bond asset class (cf. Fama and French, 1993). Though this effect was a priori not intuitive, we saw that rational explanations have been proposed.

2.1.3 Momentum

2.1.3.1 Seminal Papers on Momentum and Review of the Empirical Evidence

In this section, we present an overview of the seminal papers on momentum starting with the pioneering work of Jegadeesh and Titman (1993).

Jegadeesh and Titman (1993) discuss that if stock prices overreact or underreact to information, then profitable trading strategies that select stocks based on their past returns will exist. The authors investigate the efficiency of the stock market by examining the profitability of a number of strategies that buy past winners and sell past losers[35]. The authors also examine another set of strategies that skip a week[36] between the portfolio formation period and the holding period.

34 - While the Zhang (2005) and Cooper (2006) papers are closely related, the former focuses on the relationships between the firm's systematic risk and both its book-to-market ratio and its excess capital capacity and the latter on the relationship only between book-to-market and risk. Furthermore, Zhang models adjustment costs of both investment and disinvestment as convex for the sake of analytical tractability. Instead, actual investment behavior exhibits periods of inaction interrupted by investment spikes, behavior which is consistent with the existence of non-convex adjustment costs and irreversibility. Cooper incorporates exactly these types of costs as well as complete or partial investment irreversibility.

35 - The strategies considered select stocks based on their returns over the past J months (where J goes from 1 to 4 quarters) and hold them for K periods (where K goes from 1 to 4 quarters).

36 - By skipping a week, the authors avoid some of the bid-ask spread, price pressure and lagged reactions effects.

2. Equity Risk Factors and Factor Indices

The profits of all these strategies were calculated for both series of buy and hold portfolios and a series of portfolios that were rebalanced monthly to maintain equal weights.

The authors show that most of the returns of the zero-cost portfolios (i.e. long winner minus short losers) are positive and many of the t statistics are large. Furthermore, they show that the holding period returns are slightly higher when there is a 1 week lag between the formation period and the holding period than when the formation and holding period are contiguous.

Carhart (1997) explains the short term persistence in equity mutual fund returns with common factors in stock returns and investment costs. He finds that buying last year's top decile mutual funds and selling last's year bottom decile funds yields a return of 8% per year. This return is made of differences in the market value and momentum of stocks for 4.6%, differences in expense ratios for 0.7% and differences in transaction costs for 1%. Overall, the author argues that the short-term persistence in mutual fund performance does not reflect superior stock-picking skill. Rather, almost all of the predictability in mutual fund returns is rationally explained by common factors in stock returns, persistent differences in mutual fund expenses and transaction costs. Carhart concludes that "only the strong, persistent underperformance by the worst return mutual funds remains anomalous".

Finally, Rouwenhorst (1998) tests the results of Jegadeesh and Titman (1993) by using an internationally diversified relative strength portfolio which invests in medium-term Winners and sells past medium-term Losers and find that the portfolio earns around 1 percent per month. The author uses data from 12 countries (i.e. Austria, Belgium, Denmark, France, Germany, Italy, Netherlands, Norway, Spain, Sweden, Switzerland and the United Kingdom) and shows that the momentum in returns is to be found in all 12 countries of the sample. The momentum effect exists whatever the size deciles considered. However, it is stronger for small firms than it is for large firms. The persistence of performance is observed for about one year, and may not be explained as a premium to conventional risk exposures. Indeed, when controlling for market risk or exposure to a size factor, the authors observe an increase of the abnormal performance of relative strength portfolios.

Having discussed the key papers that uncovered momentum, in the next section we provide a detailed description of the different approaches used to construct momentum portfolios.

2.1.3.2 Construction of Momentum Factor Portfolios and Improvements to the Basic Momentum Factor

In this section we present the momentum portfolio formation adopted by the seminal paper of Jegadeesh and Titman (1993) and compare it to two recent portfolio formation methodologies used by Blitz, Huij and Martens (2011) and Daniel and Moskowitz (2013).

Before introducing the portfolio construction step, we briefly summarise the above mentioned papers[37] by focusing on the motivations that led such authors to develop new momentum portfolio construction techniques.

On the one hand, Blitz, Huij and Martens (2011) classify stocks based on

37 - Jegadeesh and Titman (1993) has already been discussed in the previous section.

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their residual momentum. The reason, presented in their papers, for adopting this classification methodology is due to the results of Grundy and Martin (2001), who evidenced that the momentum factor has a considerable time-varying exposure to the Fama-French book-to-market and size factors. In particular, the exposure is positive when the returns of these factors are positive during the period where the momentum strategy is initiated. Similarly, the exposure is negative, when the returns of the factors are negative during the initiation. As a result, the momentum strategy will be profitable only if the factor returns were positive both during the formation and holding period of the strategy, or negative during both. In the event of a modification of the sign of factor returns between the two periods, the momentum strategy will generate losses. Blitz, Huij and Martens (2011) carried out several robustness checks and found the following results: (1) the risk-adjusted profits of residual momentum are about three times as large as those produced by the total return momentum; (2) residual momentum is more consistent over time; and (3) residual momentum is less concentrated in the extremes of the cross-section of stock returns. This is because residual momentum has smaller time-varying factor exposures than total return momentum (as it is nearly market neutral by construction), which reduces the volatility of the strategy.

On the other hand, Daniel and Moskowitz (2013) argue that if strong positive returns and Sharpe ratios are observed most of the time for momentum strategies, occasional strong reversals or crashes may also happen. The authors suggest that what may drive the crashes of the momentum strategies is the changing betas of the momentum portfolios. In line with the intuition presented in Grundy and Martin (2001), Daniel and Moskowitz (2013) show that if we observe a significant market decline during the formation period of the momentum strategy, the firms that perform best are liable to be low-beta firms, while the firms that follow the decline of the market are liable to be high-beta firms. As a result, the momentum portfolio is likely to be long low-beta stocks (past winners) and short high-beta stocks (past losers) (which is verified empirically by the authors).

Hence, a sudden recovery of the market will cause losses in momentum strategies because they have a conditionally large negative beta. In order to address this issue, Daniel and Moskowitz (2013) propose an optimal dynamic momentum strategy which is discussed in Table 6. The authors find that their optimal dynamic strategy significantly outperforms the standard static momentum strategy, as measured by the Sharpe ratio that is about twice as large as that of the standard strategy. There are two explanations for this result. First, the dynamic strategy smoothes the volatility of the momentum portfolio; second, it exploits the strong forecast ability of the momentum strategy's Sharpe ratio. The authors find consistent results across time periods, markets and asset classes.

In the table below, we summarise the construction steps of the momentum starting with the standard approach of Jegadeesh and Titman (1993).

Regardless of the method adopted to construct momentum portfolios, there is still an ongoing debate in the literature on what drives momentum returns. In the coming section, we present a brief literature review on this matter.

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Table 6: The table shows some examples of new construction methodologies of the momentum-tilted portfolios taken from recent literature (e.g. Blitz, Huij and Martens (2011), Daniel and Moskowitz (2013) and Han and Zhou (2014)) as well as the standard method of Jegadeesh and Titman (1993).

Authors	Portfolio Formation-Standard Approach
Jegadeesh and Titman (1993)	At the beginning of each month t, the securities are ranked in ascending order on the basis of their returns in the past J months (where J goes from 1 to 4 quarters). Based on these rankings, ten decile portfolios are formed that equally weight the stock in each decile. In each month t, the strategy buys the winner portfolio and sells the loser portfolio, holding this position for K months (where K goes from 1 to 4 quarters). In addition, the strategy closes out the position initiated in month t-K. Hence, under this trading strategy, the authors revise the weights on 1/K of the securities in the entire portfolio in any given month and carry over the rest from the previous month.
	Portfolio Formation-Improved Approach
Blitz, Huij and Martens (2011)	The authors allocate stocks to mutually exclusive decile portfolios based on their residual returns over the preceding 12 months excluding the most recent month. Residual returns are estimated each month for all eligible stocks using the Fama and French three-factor model: $$r_{i,t} = \alpha_i + \beta_{1,i} * RMRF_t + \beta_{2,i} * SMB_t + \beta_{3,i} * HML_t + \varepsilon_{i,t}$$ Where $r_{i,t}$ is the return on the stock i in month t in excess of the risk-free rate, $RMRF_t$, SMB_t and HML_t are the excess returns on factor-mimicking portfolios for the market, size and value in month t. $\varepsilon_{i,t}$ is the residual of stock return i in month t. The authors estimate the regression over 36 month rolling windows i.e. over the period from t-36 to t-1 so that there are a sufficient number of return observations to obtain accurate estimates for stock exposures to the market, size and value. The top (bottom) decile contains 10% percent of stocks with the highest (lowest) 12-1M residual return standardised by its standard deviation over the same period. Each decile portfolio is equally weighted. The authors form the deciles using monthly, quarterly, semi-annually and yearly holding periods using the overlapping portfolios approach of Jegadeesh and Titman (1993).
Daniel and Moskowitz (2013)	The authors first start by ranking stocks according to their cumulative returns from 12 months before to one month before the formation date. The firms with the highest ranking go into the Winner portfolio and those with the lowest ranking go to the Loser portfolio. The authors then design a strategy which dynamically adjusted the weights of the basic WML (winners-minus-losers) strategy using the forecasted return and volatility of the WML strategy. The optimal weights that are derived from the optimal function (which maximises the Sharpe ratio) are defined as follows: $$w^*_{t-1} = \left(\frac{1}{2\lambda}\right) * \frac{\mu_{t-1}}{\sigma^2_{t-1}}$$ Where μ_{t-1} is the conditional expected return, σ^2_{t-1} is conditional variance of the WML portfolio return over the coming month and λ is the time invariant scalar that controls the unconditional risk and return of the dynamic portfolio. As a proxy for the expected return, the authors use the interaction between the bear market indicator (which is an indicator function that equals 1 if the cumulative value-weighted (VW) index return in the 24 months leading up to the start of month t is negative and is zero otherwise) and the market variance over the preceding 6 months. To estimate volatility of the WML series, the authors form a linear combination of the forecast future volatility from a fitted GJR-GARCH process with the realised standard deviation of the 126 daily returns preceding current month.
Han and Zhou (2014)	The authors follow the methodology of Jegadeesh and Titman (1993) to construct momentum portfolios. The stop-loss strategy proposed by the authors focuses on the Winners and Losers arms of the momentum (winners minus losers portfolio). They use the daily open and close prices to determine whether or not the stop-loss trade is triggered for each stock in either portfolio on each trading day (the loss level L considered is 10%). On each trading day before the end of the next month, they compute the return as: $$R^X_t = \frac{P^X_t - P_0}{P_0} \quad X = O, C$$ Where P_0 is the price at the beginning of the month, P^X_t is either the open or the close price of the day. If both R^O_t and R^C_t then they keep the stock in the portfolio the next day. However if R^O_t > -L and $R^C_t \leq$ -L then they close out the position and assume the stock is sold at exactly L=10% loss during the day. If $R^O_t \leq$-L they also close out the position and assume the stock is sold at the open R^C_t. Once the stop-loss trade is triggered on any day, the stock is either sold (winners) or bought (losers) to close the position. The proceeds are invested in a risk-free asset until the end of the month. The stop-loss strategy limits the monthly losses of the momentum strategy and also limits substantially the downside risk. As a result, the Sharpe ratio of the stop-loss momentum strategy is double that of the standard momentum strategy.

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2.1.3.3 Economic Rationale for Momentum Risk Premium:

According to Liu and Zhang (2008), the momentum literature has mostly followed the conclusions of Jegadeesh and Titman, who describe momentum profits as a behavioural under-reaction to firm-specific information. The reason is probably that empirical literature has yet to evidence the risk momentum may be rewarded. For example, the momentum cannot be explained by market risk, as shown by Jegadeesh and Titman, nor by the Fama and French (1996) three-factor model. Similarly, Grundy and Martin (2001) and Avramov and Chordia (2006) find no link between time-varying exposures to common risk factors and momentum profits.

Liu and Zhang (2008) review the papers that explore risk-based explanations of momentum. According to Conrad and Kaul (1998), the cross-sectional variations in the mean returns of individual securities can potentially drive momentum. Ahn, Conrad and Dittmar (2003) find that the non-parametric risk adjustment they propose can account for roughly half of the momentum profits. Chordia and Shivakumar (2002) show that the profits of the momentum strategies are explained by common macroeconomic variables that are related to the business cycle. Pastor and Stambaugh (2003) explain half of the momentum profits by the existence of a liquidity risk factor. Bansal, Dittmar and Lundblad (2005) explain the average return differences across momentum portfolios by the existence of a consumption risk embodied in cash flows. Finally, Chen and Zheng (2008) document that winner minus loser portfolios have positive exposures on a low-minus-high investment factor. Liu and Zhang (2008) find that the combined effect of the growth rate of industrial production (MP) loadings and the risk premia accounts for more than half of the momentum profits. Mahajan, Petkevitch and Petkova (2011) show that momentum stocks are exposed to aggregate default risk in the economy. Recently, attempts have been made to tie the profitability of momentum strategies to risks related to firm fundamentals. In particular, such risks may arise from the investment patterns of firms whose stocks display momentum and which lead to higher exposure to investment specific shocks (see e.g. Li (2014), and Liu and Zhang (2014)).

2.1.4 Low-Risk Stocks

2.1.4.1 Empirical Evidence

There is an interesting discrepancy that exists in the academic literature between the theoretical predictions from standard asset pricing models regarding the risk-return relation and the results obtained by researchers who have analysed this relation from a purely empirical perspective.

On the one hand, theory unambiguously suggests a positive relation between risk and return, and this relation should hold for a large variety of risk measures, including systematic, specific and total risk measures, as well as volatility-based risk measures and risk measures involving higher-order moments. Standard asset pricing models first suggest that systematic risk should be (positively) rewarded, that is stocks with higher betas should earn a higher expected return. This prediction applies in both the CAPM single-factor equilibrium model (Sharpe (1964)) and multi-factor models supported by equilibrium arguments (Intertemporal Capital Asset Pricing Model, Merton (1973)) or arbitrage arguments (Arbitrage Pricing Theory, Ross (1976)).

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Subsequently, a series of papers have underlined the explanatory power of idiosyncratic, as opposed to systematic, risk for the cross section of expected returns. In particular, Merton (1987) shows that an inability to hold the market portfolio, whatever the cause, will force rational investors to care about total risk to some degree in addition to market risk so that firms with larger firm-specific risk require higher average returns to compensate investors for holding imperfectly diversified portfolios (see also Malkiel and Xu (2006) or Boyle, Garlappi, Uppal and Wang (2009) for more recent references, as well as Barberis and Huang (2001) for a similar finding from a behavioural perspective). Taken together, these results suggest that total volatility, which is the model-free sum of systematic volatility explained by a factor model, and idiosyncratic volatility, should also be positively rewarded (see Martellini (2008) for an analysis of the implications of this finding for portfolio selection).

On the other hand, a number of older as well as more recent papers have reported a series of puzzling, or at least, contradictory findings from an empirical perspective. First, the "low-beta anomaly" stipulates that the relation between systematic risk as measured by a stock beta and return is much flatter than predicted by the CAPM (see early papers by Black (1972), Black, Jensen, and Scholes (1972), as well as Haugen and Heins (1975), who claim that the relation was not merely flat in their sample period, but actually inverted). More recently, Ang, Hodrick, Ying, and Zhang (2006, 2009) have drawn new attention to these results with a focus on the specific risk component, finding that stocks with high idiosyncratic volatility have had "abysmally low returns" in longer U.S. samples and in international markets. This result is now widely known as the "idiosyncratic volatility puzzle" or "iv puzzle" in short. Moreover, Clarke, de Silva and Thorley (2010) argue that a low idiosyncratic risk factor adds value in multi-factor analysis of portfolio performance. Yet other papers have documented a rather flat or even negative relation between total (as opposed to specific) volatility and expected return, an anomaly that some call the "total volatility puzzle", or "tv puzzle" in short. In early work, Haugen and Heins (1972, 1975) analyse pitfalls in commonly used cross-sectional tests of the risk-return relation, and express doubts regarding the existence and significance of the risk premia implied by standard asset pricing models. In a more recent study, Haugen and Baker (1996) find a positive or negative average payoff to total volatility in the cross section of stock returns depending on the dataset under consideration, but they find that total volatility is less important than other factors such as valuation ratios, growth potential, and returns momentum or reversal effects (see also Haugen and Baker (1991, 2009) for related results). In addition, when they take a multi-factor approach to returns prediction, they find that stocks with high predicted returns tend to display low volatility. Blitz and van Vliet (2007) analyse a twenty-year period and show results in which portfolios of low-volatility stocks have higher returns than portfolios of high-volatility stocks, even though they do not provide formal significance tests for differences in returns. Similarly, Baker, Bradley, and Wurgler (2011) find that portfolios formed by sorting stocks by past volatility display higher returns for the low-volatility quintile over the subsequent month than for the high-volatility quintile. Bali, Cakici, and Whitelaw (2010) investigate

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a measure of lottery-like return distributions, which is highly correlated with other risk measures, and find that it is also associated with poor performance. Asness, Frazzini and Pedersen (2013) find that a "betting against beta" factor which is long the low-beta stocks and short the high-beta stocks earns a positive reward in the long run.

2.1.4.2 Constructing Low Volatility Portfolios

Eiling (2006)). In a related effort, Cao and Xu (2010) decompose idiosyncratic volatility into its short- and long-term components and find a positive relation between the long-term component and expected stock returns. Extending these results to higher-order moments, it has also been shown that low idiosyncratic-volatility stocks usually have low skewness (Boyer, Mitton, and Vorkink (2010), Chen, Hong, and Stein (2001)) or unfavourable exposure to shocks in aggregate market

Authors	Construction Methodology of Factor-Tilted Portfolios
Chow, Hsu, Kuo and Li (2014)	**Minimum Variance Strategies.** Using the shrinkage methods of Ledoit and Wolf (2004), Wolf (2004) and Clarke *et al.* (2006), the authors compute the covariance matrices for the 1,000 largest companies provided by the CRSP database, using trailing five years of monthly returns. They then use quadratic programming to compute minimum variance long-only portfolios. **Heuristic Low Volatility Methodologies.** The authors select the 200 lowest beta stocks from the 1,000 largest companies and construct portfolios by weighting them by the inverse of their volatility. They also propose similar methodology using stock volatility, instead of beta.
Ghayur, Heaney and Platt (2013)	The methodology is based on quantile portfolios obtained by ranking stocks based on trailing 12-month daily volatility to form deciles of approximately 100 stocks each, assigning the lowest volatility stocks to decile 1. The authors then construct portfolios by attributing stocks a weight inversely proportional to their volatility, instead of using cap-weighting.

2.1.4.3 Robustness of the Volatility Puzzle:

More recently, a number of papers have provided various explanations to the "iv puzzle", and the "tv puzzle" ("total volatility puzzle"). First of all, a number of recent papers have questioned the robustness of Ang *et al.* (2006, 2009) results. Among other concerns, the findings are not robust to changes to data frequency, portfolio formation, the screening out of illiquid stocks (Bali and Cakici (2008)) or to adjusting for short-term return reversals (Huang *et al.* (2010a)) or to past maximum returns (Bali, Cakici, and Whitelaw (2010)). Other authors change the short-term measure of volatility in Ang *et al.* (2006) with measures obtained over longer horizons and then find a positive relation (Fu (2009), Spiegel and Wang (2005), Brockmann and Schutte (2007), volatility (Barinov (2010)). In terms of total risk measures, Boyer, Mitton and Vorkink (2010) and Connrad, Dittmar and Ghysels (2008) also provide converging empirical evidence that individual stocks' skewness and kurtosis is indeed positively related to future returns. More recently, authors have also looked at downside risk measures incorporating volatility, skewness and kurtosis. Bali and Cakici (2004) show a significant positive link between total risk, as measured by Value-at-Risk (VaR), and stock returns over annual horizons, a finding that is robust to book-to-market, size and liquidity effects. Similarly, Chen, Chen, and Chen (2009) show that downside risk measures have more cross-sectional explanatory power than beta or volatility measures, while Huang *et al.* (2010b) find a significant positive premium for extreme downside

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risk (a stock's Value-at-Risk measured using extreme value theory) in the cross section of stock returns even after firm size, book-to-market, reversal, momentum, and liquidity effects are controlled for. Novy-Marx (2014) finds that returns to low volatility portfolios are fully explained by common risk factors including the market, size, value and profitability factor (also see Section 2.1.6 below). In particular, he finds that high-volatility stocks tend to be unprofitable small-cap growth firms whose factor exposures explain their poor returns compared to low volatility stocks.

Most relevant to the discussion of the premium on low volatility stocks is a paper by Huang *et al.* (2010a), who find that the iv puzzle disappears after short-term return reversals are controlled for. More specifically, they report that "return reversals can explain both the negative relation between value-weighted portfolio returns and idiosyncratic volatility and the insignificant relation between equal-weighted portfolio returns and idiosyncratic volatility". Another notable paper is by Cao and Xu (2010), who decompose stock-specific volatility into long- and short-run components, and who find that while "the short-run idiosyncratic risk component is negatively related to stock returns, stocks with high long-run idiosyncratic-risks do have large future returns". Similar to results by Huang *et al.* (2010a) and Bali and Cakici (2008), Li, Sullivan, and Garcia-Feijoo (2014a) show that the low volatility effect is at best weak, especially when using equal-weighted (rather than cap-weighted) portfolios and when holding portfolios for longer time horizons. Moreover, they find that the attractive returns of low volatility stocks are mostly driven by small-cap and low liquidity stocks posing significant challenges to implementing strategies that may benefit from the premium.

While some authors have questioned the robustness of the low volatility puzzle, other authors have explained why it can be expected to exist in the first place. In the coming section, we present an overview of the explanations put forward to support the existence of the volatility effect.

<u>2.1.4.4 Economic Rationale for Volatility Factor:</u>

The focus of this section is on providing an overview of explanations presented in the literature for the possibility that the fundamental risk-return relation is, in fact, not positive, but flat, or even negative.

Early in the CAPM literature, Brennan (1971) and Black (1972) already showed that leverage (or borrowing) constraints may lower the slope of the security market line, causing low-beta stocks to have higher returns than predicted by the model. Examples of leverage restrictions are margin rules, bankruptcy laws that limit lender access to a borrower's future income and tax rules that limit deductions for interest expenses. Black (1993) revisits this subject and finds that leverage constraints have tightened rather than weakened over time.

According to Blitz, Falkenstein and van Vliet (2014), the intuition presented by these authors can be summarised as follows: in the presence of borrowing constraints, investors who want to increase their return will tilt their portfolio towards high-beta securities in order to collect more of the equity risk premium. This behaviour generates an extra demand for high beta securities and a reduced demand for low-beta securities, which, according

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to them, may explain a flatter security market line than predicted by the CAPM. Indeed, these results have been recently confirmed by Frazzini and Pedersen (2014) who also explain the volatility effect by the existence of leverage constraints.

Others argue that restrictions on short-selling help to distort the risk-return relation. Blitz, Falkenstein and van Vliet (2014) present a review. For instance, according to De Giorgi and Post (2011), short-selling constraints result in a concave relation between risk and return. Hong and Sraer (2012) show that high-beta assets experience a greater divergence of opinion about their pay-offs, than low-beta assets, as divergence of opinion is likely to increase with risk. As a result, high-risk stocks are more likely to be overpriced than low-risk stocks. Thus, the model of Hong and Sraer (2012) also predicts that high beta assets are more subject to speculative overpricing than low-beta ones.

Another stream of the literature advances that the risk-return relation as predicted by the CAPM may not hold because the CAPM assumption on investor utility is not a realistic representation of agent's behaviour. In fact, the CAPM assumption states that investors are risk-averse, maximise the expected utility of their absolute wealth, and care only about the mean and variance of return. However, the literature (see Blitz, Falkenstein and van Vliet (2014) for a review) argues first that the volatility effect arises because people consider that their wealth relative to others is more important than their absolute wealth (Falkenstein (2009); Brennan (1993); Brennan, Cheng and Li (2012)). Second, some mention that the volatility effect occurs because investment professionals do not necessarily behave in a risk-averse manner for their clients. Indeed, they rather seek to maximise the value of their own option-like incentive contracts (Baker and Haugen (2012); Hsu, Kudoh and Yamada (2012); Falkenstein (2009)). Finally, the remaining literature recognises that investors may give attention to other measures than the mean and variance of return (e.g. skewness, downside risk and semi-variance) and this may be the reason behind the volatility effect (Blitz and van Vliet (2007), Falkenstein (2009), Kumar (2009), Baker, Bradley and Wurgler (2011) and Ilmanen (2012)).

Furthermore, some papers makes the case for the volatility effect by challenging the other CAPM assumption that states that investors rationally process the available information. In fact, such an assumption has been strongly confronted as the rational investment decision making process seems to be plagued by irrational behavioural biases present in the market such as "attention-grabbing stocks" where investors are net buyers of attention-grabbing stocks, such as stocks in the news, stocks experiencing high abnormal trading volume, or stocks with extreme recent returns (Barber and Odean (2008)), "representativeness bias" where investors rely more on appealing anecdotes than on statistics to trade stocks (Tversky and Kahneman (1983) and Kahneman, Slovic and Tversky (1982)) or "overconfidence" where investors believe that they are capable of successful stock picking, this overconfidence will lead them to pick more volatile stocks for the alpha generation purposes (Falkenstein (2009)). Li, Sullivan and Garcia-Feijoo (2014b) report evidence that when trying to explain the returns of low volatility portfolios, the covariance of returns with a low-risk factor does not add any explanatory power compared

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Table 7: The table provides a summary of the definitions of the different types of liquidity risk considered in the following papers: Amihud (2002), Acharya and Pedersen (2005), Roll (1984), Pastor and Stambaugh (2003) and Ibbotson et al. (2013)

Authors	Definitions
Amihud (2002)	Amihud defines stock illiquidity as the average ratio of the daily absolute return to the (dollar) trading volume on that day. This ratio gives the absolute (percentage) price change per dollar of daily trading volume, or daily price impact of the order flow. The Amihud Illiquid measure is defined as follows: $$Illiq_y^i = \frac{1}{Days_y^i}\sum_{d=1}^{Days_y^i}\frac{\lvert R_{dy}^i\rvert}{V_{dy}^i}$$ Where R_{dy}^i is the return on stock i on day d of year y and V_{dy}^i is the respective daily volume in dollars.
Acharya and Pedersen (2005)	AP(2005) consider four types of liquidity risks: The expected relative liquidity cost (or liquidity level) for each stock computed using the Amihud Measure. The authors normalise the Amihud measure in order to directly measure the cost of trade as opposed to the cost of selling only. The covariance between asset illiquidity "i" and market illiquidity "M" (i.e. $cov(c_{t+1}^i, c_{t+1}^M)$). This affects returns positively because investors want to be compensated for holding a security that becomes illiquid when the market in general becomes illiquid. The covariance between a security return and market illiquidity (i.e. $cov(r_{t+1}^i, c_{t+1}^M)$). This affects returns negatively because investors are willing to accept a lower return on an asset with a high return in times of market illiquidity. The covariance between a security's illiquidity and the market return (i.e. $cov(c_{t+1}^i, r_{t+1}^M)$). This affects returns negatively because investors are willing to accept a lower return on a security that is liquid in a down market.
Pastor and Stambaugh (2003)	The paper focuses on market illiquidity (or systematic liquidity risk) as opposed to the level of liquidity (or stock liquidity). The authors focus on the aspect of liquidity associated with temporary price fluctuations induced by order flow (proxied by the volume of the stock). The aggregate liquidity measure is a cross-sectional average of individual stock liquidity measures. The intuition is that each stock's liquidity in a given month represents the average effect that a given volume on a day d has on the return for day d+1. The idea is that a lower liquidity is reflected in a greater tendency for order flow in a given direction on day d to be followed by a price change in the opposite direction on day d+1. For a formal definition of liquidity, we refer the reader to the appendix.
Ibbotson *et al.* (2013)	The authors use the annual stock turnover as a measure of liquidity, where annual share turnover is the sum of the 12 monthly volumes divided by each month's shares outstanding. The liquidity measure adopted by the authors focuses on the stock characteristic itself rather than the stock sensitivity to a liquidity factor (i.e. beta) or market illiquidity.
Roll (1984)	The paper presents a method for inferring the effective bid-ask spread directly from a time series of market prices where the effective bid-ask spread is the spread faced by the dollar-weighted average investor who trades at the observed prices (either bid or ask). The formula is defined as follows: $$covariance\ (\Delta p_t, \Delta p_{t+1}) = -\frac{s^2}{4}$$ Where Δ_{p_t} represent the price changes between t and t-1 and s the bid-ask spread. The intuition is that the effective bid-ask spread can be inferred from the first-order serial covariance of prices changes provided that the market is efficient.

to using the risk characteristics alone. They conclude that the evidence is more consistent with mispricing than with a common risk factor explanation of the low volatility effect.

The low volatility effect has been evidenced both in the US and on international markets. Though this effect seems to be in contradiction with portfolio theory that states that a stock's expected return should be proportional to its systematic risk (beta), several explanations were proposed in the literature to explain this volatility effect.

Concerning the robustness of the factors in general, it should be noted that the existence of the factor effect may be in the first place the result of data mining and

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Table 8: The table provides a summary of the methodologies used to construct factor-tilted portfolios. The papers considered are: Amihud (2002), Acharya and Pedersen (2005), Roll (1984), Pastor and Stambaugh (2003) and Ibbotson et al. (2013)

Authors	Construction Methodology of Factor-Tilted Portfolios
Amihud (2002)	The author does not construct any factor-tilted portfolios.
Acharya and Pedersen (2005)	The authors form 25 illiquidity portfolios for each year y by sorting stocks with price, at the beginning of the year, between 5 and 1000 dollars, and return and volume data in year y-1 for at least 100 days. Then, they compute the annual illiquidity for each stock as the average over the entire year y-1 of daily illiquidities where illiquidity is computed using Amihud measure (defined above). The eligible stocks are then sorted into 25 portfolios based on year y-1 illiquidities. The authors also form 25 "illiquidity variation" portfolios by ranking the stocks each year based on the standard deviation of daily illiquidity measures in the previous year. Then for each portfolio, they compute the returns by equally weighting or value weighting stocks.
Pastor and Stambaugh (2003)	The authors sort stocks according to their sensitivities (β_i^L) to the innovations in aggregate liquidity L_t. There are two steps: (1) portfolio formation and (2) post-ranking (1) Portfolio formation: the β_i^L captures the asset co-movement with innovations in aggregate liquidity where β_i^L is allowed to be time-varying. The authors form portfolios according to two types of betas: "predicted" betas and "historical" betas. Here we will only discuss "predicted" betas as "historical" betas are a special case of the predicted betas. For more information on predicted betas, we refer the reader to the appendix. (2) Post-Ranking: Once the stocks are sorted according to their "predicted" liquidity betas, they are assigned to 10 decile portfolios. The portfolio returns are computed over the following 12 months, after which the portfolio formation procedure is repeated. The post-ranking returns are linked across years generating a single return series for each decile covering the whole period. The portfolios are value-weighted.
Ibbotson *et al.* (2013)	The construction methodology consists of a two-step algorithm: (1) selection (prior) year (2) the performance (current) year. (1) For each selection year, they examine the top 3500 US stocks by year-end market cap. From this universe, they record the liquidity for each stock as the annual share turnover. They then rank the universe and sort into quartiles so that each stock within the selection-year portfolio received quartile number for turnover. (2) In the performance year, the portfolios selected are equally weighted at the beginning of each year and passively held. Then they record the returns at the end of the performance year for each selection-year portfolio.
Roll (1984)	The author does not construct any factor-tilted portfolios.

may be related to the temporary existence of extreme conditions on financial markets. In addition, the risk premium evaluation is not free of the choice of the starting date and the ending date of the period, as return computations are sensitive to this choice. Another problem may be related to the use of proxies to capture a given factor exposure, as practical implementation may deviate considerably from factor definition. In addition, there may be interaction between two factors, as observed with size and liquidity factors (small stocks are less liquid than large stocks, Amihud and Mendelson, 1986).

2.1.5 Liquidity Factor:

2.1.5.1 Review of Liquidity Definitions

Liquidity is an elusive concept and, as Amihud (2002) emphasises, it also has many facets (e.g. depth, trading costs, etc.) that cannot be captured in a single measure.

In the following table, we provide a comprehensive definition of the different liquidity measures adopted in the academic literature with a focus on Amihud (2002), Acharya and Pedersen (2005), Pastor and Stambaugh (2003), Roll (1984) and Ibbotson *et al.* (2013). The goal of such a table is to understand which aspect of liquidity matters the most and that one needs to focus on in order to construct illiquidity factors or illiquidity tilted portfolios.

2.1.5.2 Constructing Illiquidity Factor Portfolios from Stocks.

In this section, we provide a detailed explanation on how different authors

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Table 9: The table provides a summary of the results of the impact of illiquidity risk on the cross section of stock returns. The papers considered are Amihud (2002), Acharya and Pedersen (2005), Pastor and Stambaugh (2003) and Ibbotson et al. (2013).

Authors	Evidence of Illiquidity Risk Premium
Amihud (2002)	The author performs different tests: (1) Cross-sectional impact of illiquidity on stock returns: The model regresses stock returns on : (a) the average market illiquidity (i.e. average of Amihud Illiquid measure across stocks) in each year, (b) size of the stocks, (c) BETA of the stocks (where "BETA for each stock" is equal to the "BETA of the size-sorted portfolio" in which it belongs to and where the "BETA of the size-sorted portfolio" is measured by taking the slope of the regression of size-sorted portfolio returns on the market portfolio), (d) the standard deviation of daily return of stock i in year y, (e) the dividend yield of each stock i in year d and (f) past stock returns. The results show that market illiquidity is priced in the cross section of stock returns. The illiquidity coefficient is highly significant and positive. (2) The effect of market illiquidity over time on the expected stock return: Although in this study, we focus on the cross-sectional effect of illiquidity on stock returns, it is also important to mention the time series effect as liquidity is very persistent over time. The intuition presented in the paper is that if investors anticipate higher market illiquidity, they will price stocks (today) so that they generate higher expected returns. Therefore, expected stock excess returns are an increasing function of expected market illiquidity. Liquidity is persistent, therefore higher illiquidity in one year raises expected illiquidity for the following year. The author argues that if higher expected illiquidity causes ex-ante stock returns to rise, stock prices should fall when illiquidity unexpectedly rises. Therefore, the author conjectures that there should be a negative relationship between unexpected illiquidity and contemporaneous stock returns. The author tests both implications and finds that (1) expected stock returns are an increasing function of expected market illiquidity (2) unexpected market illiquidity has a negative effect on stock prices.
Acharya and Pedersen (2005)	The results show that the sort on past illiquidity successfully produces portfolios with monotonically increasing average illiquidity from portfolio 1 to 25. Furthermore, they find that illiquid stocks have a lot of commonality in liquidity with the market (i.e. high $\beta_2 = \frac{cov(c^i_{t+1}, c^M_{t+1})}{Var(r^M_{t+1} - c^M_{t+1})}$), a lot of return sensitivity to market illiquidity (i.e. high $\beta_3 = \frac{cov(r^i_{t+1}, c^M_{t+1})}{Var(r^M_{t+1} - c^M_{t+1})}$) and a lot of liquidity sensitivity to market returns (i.e. high $\beta_4 = \frac{cov(c^i_{t+1}, r^M_{t+1})}{Var(r^M_{t+1} - c^M_{t+1})}$). The authors run a cross-sectional regression on the test portfolios (i.e. illiquidity portfolios) and find evidence that liquidity risk matters over and beyond market and liquidity level. Furthermore, the authors find that the liquidity adjustment introduced in the CAPM framework improves the fit (as compared to the CAPM) for illiquid portfolios. In fact, the difference in annualised cross-sectional return between the least liquid and most liquid portfolios can be attributed to: The commonality between portfolio illiquidity and market illiquidity (i.e. β_2) for 0.08% The sensitivity of the portfolio return to market illiquidity (i.e. β_3) for 0.16% The sensitivity of the portfolio illiquidity to market return (i.e. β_4) for 0.82% Thus, the total effect of liquidity risk is 1.1% per year. Furthermore, the difference in annualised expected returns between the least and most liquid portfolio that can be attributed to expected liquidity (or liquidity level) is 3.5%. Therefore, in total the overall effect of liquidity risk and expected illiquidity is 4.6% per year.
Pastor and Stambaugh (2003)	The authors run a cross-sectional regression of the sorted portfolios on the aggregate liquidity innovations, market and FF factors and find that liquidity betas increase across decile portfolios consistent with the ranking. The "10 -1" spread, which goes long high liquidity beta and short low liquidity beta, has an overall liquidity beta of 8.23 (with t-stat of 2.37). Furthermore, the "10-1" spread has a significant and positive alpha even after including the four factors in the regression (i.e. market, FF and Momentum). The significance of alphas is robust across sub-periods. Overall, the liquidity risk premium is positive, in line with the idea that stocks with higher sensitivity to aggregate liquidity shocks offer higher expected returns[38].
Ibbotson *et al.* (2013)	The authors construct monthly returns of (1) a long/short portfolio in which the returns of the most liquid quartile are subtracted from the returns of the least liquid quartile (2) a less liquid long-only portfolio. Both constructed series are regressed on the CAPM, Fama-French and Four Factors Carhart equations and both series show that the alpha is positive and significant. The significance of the alpha implies the market, size, value and momentum cannot fully describe the set of betas needed to put together an efficient portfolio. Furthermore, the authors examine the double-sorted portfolio (i.e. combining liquidity with size, value and momentum) and find that the impact of liquidity on returns was stronger than that of the size and momentum and comparable to that of value. They conclude that liquidity is a viable alternative to size, value and momentum. Finally, they also demonstrate that less liquid portfolio could be formed at low cost.

38 -Please note that PS (2003) focus on the sensitivity of stock returns to aggregate market illiquidity and not the sensitivity of stock liquidity to market liquidity.

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construct factor-tilted portfolios. We explain how the authors select stocks according to their liquidity attributes and form portfolios based on the stock ranking.

Once the portfolios are formed according to their liquidity characteristics, the authors study the impact of illiquidity factors on the cross section of stock returns.

2.1.5.3 Empirical Evidence on the Illiquidity Premium in the Cross-Section of Stock Returns

In this section, we provide an overview on the empirical evidence of the illiquidity risk impact on the cross section of stock returns.

Regardless of the different construction methodologies of illiquidity factor-tilted portfolios, the table reveals that all papers converge towards the existence of an illiquidity risk premium priced in stock returns.

In the coming section, we empirically test such results and compare the illiquidity risk factor with that of value, size and momentum using US data.

2.1.5.5 Economic Rationale for the Illiquidity Risk Premium

Overall, we can deduce that academic research defines liquidity differently. While some papers concentrate on stock liquidity risk (e.g. Ibbotson *et al.* (2013)), others focus on market illiquidity and its co-movement with stock illiquidity (e.g. Acharya and Pedersen (2005) and Amihud (2002)). In fact, it can be quite challenging to find a unique liquidity measure that captures all illiquidity aspects (e.g. depth of market, trading costs, price impact, etc.). However, one common finding that emerges from these papers is that both stock illiquidity and market illiquidity have strong implications for stock returns, as it is expected that agents would want to be compensated for holding illiquid stocks. For instance, Acharya and Pedersen (2005) show theoretically and empirically that the persistence of liquidity implies that liquidity predicts future returns and co-moves with contemporaneous returns. This is consistent with Amihud (2002), Chordial *et al.* (2000), Hasbrouk and Seppi (2001), Huberman and Halka (1999), Pastor and Stambaugh (2003) among others. Furthermore, the persistence of liquidity also implies that returns are predictable.

2.1.5.6 Further Considerations and References

The liquidity measures discussed so far use volume data in their construction. However, the literature also points to other types of proxies that utilise high-frequency data such as quotes and transactions.

Amihud (2002) made a review. Chalmers and Kadlec (1998) find a positive link between liquidity, measured as the amortised effective spread (obtained from quotes and transactions) and stock returns.[39] Brennan and Subrahmanyam (1996) find that illiquidity has a positive impact on stock returns. Stock illiquidity is measured as the price response to order flow, and by the fixed cost of trading using intra-day continuous data on transactions and quotes. Easley et al. (1999) introduced a new measure of microstructure risk, namely the probability of information-based trading. This measure, estimated from intra-daily transaction data, reflects the adverse selection cost resulting from asymmetric information between traders,

39 -The effective spread is the absolute difference between the mid-point of the quoted bid-ask spread and the transaction price that follows. The spread is divided by the stock holding period to obtain the amortized spread.

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as well as the risk that the stock price can deviate from its full-information value. They found that the probability of information-based trading has a large positive and significant effect on stock returns.

The inconvenience of these illiquidity measures is that they require lots of data, such as quotes and transactions data (microstructure data) which are not available in most markets. Furthermore, a recent paper by Goyenco, Holden and Trzcinka (2009) provides significant evidence that both monthly and annual low-frequency measures (such as those described in Section 2.1.5.1) usefully capture high-frequency measures of transactions costs. According to the authors, the correlations between high and low-frequency liquidity measures are quite high and the mean squared error is quite low, which renders the use of high-frequency measures not very interesting.

2.1.6 Profitability and Investment Factors

In this section, we briefly review other accounting-based factors and the economic rationale that lies behind their capacity to yield risk premia. In particular, we will review the empirical evidence on investment and profitability factors in the cross section of stock returns, and the rationale for a risk premium associated with these factors.

2.1.6.1. Empirical Evidence

There is in fact ample empirical evidence suggesting that investment and profitability are important determinants of the cross section of stock returns.

On the one hand, profitability is typically proxied as return on equity (ROE) defined as net income divided by shareholders' equity (book value of equity). The corresponding factor is based on sorting stocks by ROE into portfolios and creating a zero investment strategy called profitable minus unprofitable (PMU). The outperformance of profitable over unprofitable companies has been documented in a recent paper by Novy-Marx (2013), who shows that profitable firms generate higher returns than unprofitable firms. Novy-Marx insists on the importance of using gross profits rather than accounting earnings to determine profitability. Cohen, Gompers and Vueltenhao (2002) provide similar evidence showing that – when controlling for book-to-market - average returns tend to increase with profitability. On the other hand, investment is typically defined as asset growth (change in book value of assets over previous year). The corresponding factor is based on sorting stocks by asset growth into portfolios and creating a zero investment strategy called Conservative Minus Aggressive (CMA). Cooper, Gulen, and Schill (2008) show that a firm's asset growth is an important determinant of stock returns. In their analysis, low investment firms (firms with low asset growth rates) generate about 8% annual outperformance over high investment firms (firms with high asset growth rates). Titman, Wei, and Xie (2004) show a negative relation between investment (which they measure by the growth of capital expenditures) and stock returns in the cross section. A negative relation between investment and stock returns is also documented by Xing (2008) and Lyandres, Sun, and Zhang (2008) who use yet other firm characteristics to proxy for investments. Ahroni, Grundy and Zeng (2013) show that - even when controlling for profitability and book-to-market – there is a negative relation between investment and returns.

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The empirically observed effects of investment and profitability have led other researchers to integrate these factors in multi-factor models, with some models accounting for both effects simultaneously. In the following section, we present the economic rationale behind the investment and profitability factors.

It should be noted that investment practitioners often use balance-sheet related metrics related to investment and profitability in what is termed "quality" investing. However, an important distinction should be made between many "quality" investing approaches that exist in practice and factor investing approaches that try to implement exposures to rewarded risk factors such as investment and profitability.

In fact, quality investing approaches in the industry more often than not consist of stock picking. For such quality stock picking approaches, "leading industry proponents include GMO's Jeremy Grantham, whose high quality indicators of high return, stable return, and low debt have shaped the design of MSCI's Quality Indices, and Joel Greenblatt, and his "Little Book that Beats the Market…" (Novy-Marx 2014). These approaches try to add alpha in a systematic way akin to what a stock picker does. The stock picking philosophy appears to be based on a naive belief that a systematic rebalancing of an index based on accounting data generates alpha

In contrast to such stock picking approaches, the factor-based approach is founded on asset pricing theory and tries to design factor indices or smart factor indices based on the idea that there are long-term rewarded risks, i.e. the focus is on betas (exposures with respect to common risk factors). This approach is much more humble, but also much more consistent with asset pricing theory. In factor-based investing, one does not attempt to replicate active managers but rather tries to harvest systematic risk premia that are available on the market, which is more in line with the idea of an "index."

2.1.6.2. Economic Rationale

Several authors have provided an economic rationale for these factors. It is interesting to note that the economic justification for such factors is arguably much more straightforward than the motivation for others factors such as size, value and momentum. In fact, Hou, Xue and Zhang (2012) argue that, since the investment and profitability factors should influence expected returns according to production-based asset pricing theory, using these factors "is less subject to the data mining critique than the Fama-French model". Two explanations suggesting a role for these factors are summarised below:

- Dividend Discount Model

Fama and French (2006) derive the relation between book-to-market ratio, expected investment, expected profitability and expected stock returns from the dividend discount model which models the market value of a stock as the present value of expected dividends:

$$M_t = \sum_{\tau=1}^{\infty} E(D_{t+\tau})/(1+r)^{\tau} \qquad (9)$$

Using the fact that, with clean surplus accounting, dividends equal equity earnings per share minus the change in book equity per share we have:

$$M_t = \sum_{\tau=1}^{\infty} E(Y_{t+\tau} - dB_{t+\tau})/(1+r)^{\tau} \qquad (10)$$

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and dividing by book equity yields:

$$\frac{M_t}{B_t} = \sum_{\tau=1}^{\infty} \frac{E(Y_{t+\tau} - dB_{t+\tau})/(1+r)^{\tau}}{B_t}$$

These equations lead to the following three predictions:
- Controlling for expected earnings and expected changes in book equity, high book-to-market implies high expected returns
- Controlling for book-to-market and expected growth in book equity, more profitable firms (firms with high earnings relative to book equity) have higher expected return
- Controlling for book-to-market and profitability, firms with higher expected growth in book equity (high reinvestment of earnings) have low expected returns.

• Production-based Asset Pricing
Hou, Xue and Zhang (2012) provide a more detailed economic model where profitability and investment effects arise in the cross section due to firms' rational investment policies (also see Liu, Whited and Zhang 2009). In particular, the firm's investment decision satisfies the first-order condition that the marginal benefit of investment discounted to the current date should equal the marginal cost of investment. Put differently, the investment return (defined as the ratio of the marginal benefit of investment to the marginal cost of investment) should equal the discount rate. This optimality condition means that the relation of investment and expected returns is negative: If expected investment is low, expected returns are high. Intuitively (given expected cash flows), firms with high cost of capital (and thus high expected returns) will have difficulty finding many projects with positive NPV and thus not invest a lot. The optimality condition further implies a positive relation between profitability and expected returns. High profitability (i.e. high expected cash flow relative to equity) at a given level of investment implies a high discount rate. Intuitively, if the discount rate was not high enough to offset the high profitability, the firm would face many investment opportunities with positive NPV and thus invest more by accepting less profitable investments.

2.1.6.3. Alternative Factor Models, and Relation with Carhart Factors
Many authors use alternative factor models which include profitability and/or investment factors. More often than not, authors augment standard models, such as the Fama and French three-factor model with these new factors, but some authors propose to substitute the standard factors with the new factors. It is interesting to summarise the evidence produced in this context on the dependence between the different factors.

Novy-Marx (2013) considers a four-factor model including the market factor, and (industry-adjusted) value, profitability and momentum factors. He argues that this four-factor model does a good job of explaining returns of a broad set of profitable trading strategies (including strategies seeking to exploit earnings surprises, differences in distress scores, earnings-to-price effect, etc.)

Hou, Xue and Zhang (2012) use a four-factor model including a market factor, a size factor, an investment factor, and a profitability factor, and show that the model outperforms the Fama and French three-factor model in explaining a set of well-known cross-sectional return patterns. Interestingly, they show that the investment factor is able to explain a large proportion of the value premium

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(low valuation firms do not invest a lot while high valuation firms invest a lot) and the profitability factor explains a sizable proportion of the momentum premium (momentum stocks correspond to highly profitable firms). They suggest using their four-factor model as a better alternative to the Carhart four-factor model or Fama and French three-factor model and stress the economic grounding of the investment and profitability factors.

Lyandres, Sun, and Zhang (2008) test a two factor model (market factor and investment factor) and a four-factor model (market, size, value, and investment). They show that adding the investment factor into the CAPM and the Fama and French three-factor model is useful in the context of explaining widely documented anomalies related to equity issuance.

Fama and French (2014) propose a five-factor model using the market factor, the small-cap factor, the value factor and an investment and profitability factor. Importantly, they show that the value factor is redundant in the presence of the profitability and investment factor. Despite its redundancy they argue that the value factor should be included as it is a widely used and well-understood factor in investment practice. They argue that inclusion of the size factor is empirically important despite the fact that it cannot be justified through the dividend discount model which motivates the other factors. Interestingly (but without providing any empirical test), Fama and French argue that the five-factor model should only be applied to portfolios which have a beta close to one as it does not capture the "betting against beta" (i.e. low risk) factor.

2.2 Performances and Risks of Factor Strategies

We will provide here standard risk and return characteristics (based on data from Kenneth French, etc.) for the main factors listed above. In this section, we assess the commonly used equity factors which capture the cross-sectional differences in stock returns. We start by providing a definition and risk and return analysis of the factors that will be used in this empirical study. We then study the correlation matrix and the principal component analysis of such standard equity factors (i.e. long/short factors). Finally, we analyse the return properties of the equity factors under different market conditions (i.e. bull/bear markets, high/low volatility markets, expansion/recession etc.).

2.2.1 Standard Long/short Factors: Risk and Return Analysis

2.2.1.1 Definitions

This section is purely descriptive as it only aims to describe the construction methodology of different standard long/short factors (Table 10).

2.2.1.2 Risk and Return Analysis

In this section, we present the descriptive statistics of the standard equity factors which are the market, QMJ, profitability, SMB, HML, MOM, illiquidity, BAB[40], STR and LTR. We also show the correlation matrix.

The table shows that the highest and lowest values are associated with illiquidity and momentum factors, which may imply that these factors are subject to extreme risk.

In what follows, we present a comprehensive view of the risk embedded in all factor return series. We present

40 - The BAB factor series are downloaded from Andrea Frazzini website. However, the data finishes at March 2012. In order to complete the remaining BAB series (till December 2012) and match the data length of the other considered factors (i.e. SMB, HML etc...), we replaced the missing months with the return differences of the Russell 1000 Low Beta and the Russell 1000 High beta indices.

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Table 10: The table describes the factor return series considered in this study. For all factor return series, we consider only the US universe and download the data from 1963/09 to 12/2012. The source of the data is defined for each factor in the relevant row.

Factor Return Series	Definition and Source of Data
SMB	SMB (Small-Minus-Big) is the average return on the three small portfolios minus the average return on the three big portfolios, The series are downloaded from French's website. *SMB=1/3 (Small Value + Small Neutral + Small Growth) - 1/3 (Big Value + Big Neutral + Big Growth).*
HML	HML (High-Minus-Low) is the average return on the two value portfolios minus the average return on the two growth portfolios. The series are downloaded from French's website. *HML =1/2 (Small Value + Big Value) - 1/2 (Small Growth + Big Growth)*
Momentum	Mom is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios. The series are downloaded from French's website. *Mom = 1/2 (Small High + Big High) - 1/2(Small Low + Big Low)*
Quality minus Junk (QMJ)	The construction methodology of the QMJ factor follows that of Fama and French (1993). The factor is long the top 30% high quality stocks and short the bottom 30% junk stocks within the universe of large stocks and similarly within the universe of small stocks. More information can be found on Asness and Frazzini (2013). The series are downloaded from Frazzini's website.
Profitability	The factor is constructed using four value-weight portfolios formed on size (split by NYSE median) and gross profits-to-assets (top and bottom 30% using NYSE breaks; gross profits is REVT - COGS). The factor's return is the equal-weighted average of the returns to the value-weighted large cap and small-cap profitability strategies, which buy profitable stocks and sell unprofitable stocks: *PMU = (Big Profitable - Big Unprofitable)/2 + (Small Profitable - Small Unprofitable)/2* The series are downloaded from Novy-Marx's website.
Short-Term Reversal (STR)	ST_Rev is the average return on the two low prior return portfolios minus the average return on the two high prior return portfolios. Six value-weight portfolios are formed on size and prior (1-1) returns to construct ST_Rev. The series are downloaded from French's website. *ST_Rev = 1/2 (Small Low + Big Low) - 1/2(Small High + Big High*
Long-Term Reversal (LTR)	LT_Rev is the average return on the two low prior return portfolios minus the average return on the two high prior return portfolios. Six value-weight portfolios formed on size and prior (13-60) returns to construct LT_Rev. The series are downloaded from French's website. *LT_Rev =1/2 (Small Low + Big Low) - 1/2(Small High + Big High).*
Illiquidity	Illiquidity factor return series are downloaded from the website of Robert Stambaugh and are constructed using the method of Pastor and Stambaugh-PS (2003) defined in the appendix. The series is downloaded from Stambaugh's website
BAB	A BAB factor is a portfolio that holds low-beta assets and that shorts high-beta assets. Betas are computed with respect to the CRSP value-weighted market index. Excess returns are above the U.S. Treasury bill rate. For more information on the construction methodology of the BAB factor we refer to Section 2 of the paper of Frazzini and Pedersen (2014). The series are downloaded from the Frazzini website.

Table 11: We present the descriptive statistics (i.e. mean, max, min and median) of the different factor return series considered in this study. For all factor returns series, we consider only the US universe and download the data from 1963/09 to 12/2012. The source of the data is defined for each factor in Table 9. "QMJ" stands for quality minus junk, "Mom" for momentum, "Prof" for profitability, "MKT" for market minus risk-free, "LTR" for long-term reversal, "Liq" for illiquidity factor and "STR" for short-term reversal. All construction methodologies of factor return series are defined in Table 6. We also present a t-test where the null hypothesis that data are a random sample from a normal distribution with mean 0 and unknown variance, against the alternative that the mean is not 0. Therefore, the mean values highlighted in bold indicates a rejection of the null hypothesis with 5% significance level.

	QMJ	Prof	SMB	HML	Mkt	Mom	Liq	LTR	STR	BAB
Mean	**0.39%**	**0.34%**	0.13%	**0.46%**	**0.88%**	**0.70%**	-0.02%	**0.30%**	**0.52%**	**0.87%**
Max	12.31%	6.84%	11.02%	13.87%	16.10%	18.39%	28.74%	14.47%	16.23%	15.60%
Min	-12.53%	-7.06%	-22.02%	-9.86%	-23.24%	-34.72%	-38.30%	-7.78%	-14.51%	-15.67%
Median	0.44%	0.32%	0.06%	0.40%	0.78%	0.80%	0.71%	0.17%	0.35%	0.92%

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Table 12: We present the risk statistics (e.g. Value-at-Risk, maximum drawdown, time under water, standard deviations, skewness and kurtosis) of all factor return series considered in this study. "QMJ" stands for quality minus junk, "Mom" for momentum, "Prof" for profitability, "MKT" for market minus risk-free, "LTR" for long-term reversal, "Liq" for illiquidity factor and "STR" for short-term reversal. For all factor series, we consider only the US universe and download the data from 1968/09 to 12/2012. All construction methodologies of factor return series are defined in Table 9.

	QMJ	Prof	SMB	HML	Mkt	Mom	Liq	LTR	STR	BAB
Var (95%)	4.25%	4.08%	4.88%	5.30%	7.60%	6.54%	7.28%	4.80%	5.35%	5.66%
Var (97.5%)	5.99%	4.89%	6.31%	6.39%	9.04%	8.17%	9.97%	5.95%	8.67%	7.02%
Var (99%)	7.40%	5.95%	7.83%	8.86%	11.65%	12.11%	11.41%	7.67%	44.51%	8.84%
Skew	-0.012	-0.004	-0.796	0.339	-0.502	-1.413	-1.205	0.640	0.357	-0.507
Kur	6.30	3.15	8.74	5.31	4.88	13.83	9.36	5.62	8.47	6.89
Std	2.47%	2.29%	3.14%	2.89%	4.50%	4.30%	5.68%	2.54%	3.19%	3.23%

different risk measures (e.g. Value-at-Risk, standard deviations, skewness and kurtosis) and interpret the results.

On the one hand, the table shows that market, momentum and illiquidity factors have the highest standard deviations. On the other hand, the factor returns with the lowest standard deviations are profitability and QMJ factors. Furthermore, the VaR figures indicate that the largest likely percentage losses under normal market conditions for one-month horizon with 95%, 97.5% and 99% confidence interval are associated with the market, momentum, short-term reversal and HML factors. However, the lowest likely percentage loss is that of the profitability factor.

The table also reveals that the highest negative skewness is found in momentum and illiquidity factors which implies that extreme negative values are concentrated on the left of the mean of their respective distributions. The finding on momentum seems to be consistent with the literature as the factor momentum has high downside risk (Daniel and Moskowitz 2013).

As far as the kurtosis is concerned, we see that the highest values are those of momentum and illiquidity which implies that these factors have high probability of having extreme values. Surprisingly, the market factor has one of the lowest excess kurtoses of 1.88. Overall, we note

Table 13: We present the correlation matrix of the different factor return series considered in this study. For all factor returns series, we consider only the US universe and download the data from 1963/09 to 12/2012. The source of the data is defined for each factor in Table 10. "QMJ" stands for quality minus junk, "Mom" for momentum, "Prof" for profitability, "MKT" for market minus risk-free, "LTR" for long-term reversal, "Liq" for illiquidity factor and "STR" for short-term reversal. All construction methodologies of factor return series are defined in Table 9. The significant correlation coefficients (at 5 % level) are highlighted in bold.

	QMJ	Prof	SMB	HML	Mkt	Mom	Liq	LTR	STR	BAB
QMJ	1.00									
Prof	**0.37**	1.00								
SMB	**-0.44**	**0.13**	1.00							
HML	-0.04	**-0.38**	**-0.22**	1.00						
Mkt	**-0.56**	**0.09**	**0.28**	**-0.29**	1.00					
Mom	**0.20**	0.03	**-0.16**	-0.05	**-0.13**	1.00				
Liq	**-0.18**	0.06	**0.20**	**-0.12**	**0.33**	-0.03	1.00			
LTR	0.01	0.04	-0.03	0.04	-0.06	0.03	0.00	1.00		
STR	**-0.23**	0.06	**0.21**	-0.05	0.29	**-0.29**	0.07	0.00	1.00	
BAB	**0.26**	**-0.08**	0.04	**0.30**	**-0.10**	**0.17**	**0.14**	-0.01	-0.05	1.00

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that momentum and illiquidity factors are the riskiest among all factor return series and can hide a lot of extreme values in the tails of their respective distributions.
While this section focuses on the risk analytics, in what follows, we discuss the relation between different factors.

2.2.2 Relation Between Standard Long/short Factors

2.2.2.1 Correlation Matrix
We present the correlation matrix between different factors.
The correlation matrix reveals some interesting results. First, we can see the HML is negatively correlated with that momentum factor (-0.05) which is in line with the findings of Asness and Frazzini (2013) where the authors provide evidence of the natural negative correlation of value and momentum factors.

As far as the quality factor is concerned, on the one hand, Novy-Marx (2012) finds that portfolios sorted on gross-profits-to-assets exhibit large variation in average returns. This is especially true if portfolios are sorted according to their book-to-market ratios. Their results show that the more profitable firms are also those that produce the highest returns, though they have, on average, lower book-to-market ratios and higher market capitalisations compared to unprofitable firms. Strategies based on profitability are growth strategies that can considerably improve the investment opportunity set of a value investor, by providing a goof hedging for value strategies. In the other paper, Novy-Marx (2013) finds that a simple measure such as gross profitability, defined as revenues minus cost of goods sold, scaled by assets, may be used to replace traditional value metrics to predict stock returns, producing just as good results. The authors find that strategies based on gross profitability are highly negatively correlated with strategies based on price signals, which make them of particular interest to traditional value investors. Overall, the literature points out that quality and value metrics should be negatively correlated.

Our empirical evidence shows that the correlation sign between the profitability factor and HML factor is negative (-0.38) in line with the results of Novy-Marx (2012)[41] and Novy-Marx (2013). Furthermore, the correlation sign between the QMJ factor and the HML factor is also negative (-0.04). The illiquidity factor is positively correlated with the SMB factor (0.20) which implies that illiquid stocks tend to be small stocks. Finally, the quality factor QMJ and SMB factor are negatively correlated (-0.44) which indicates that quality stocks are mostly large stocks. Furthermore, the BAB factor is negatively correlated with the market factor (-0.10). This result is in line with the construction principle of the BAB factor that goes short high-beta stocks. Finally, QMJ and BAB factors are positively correlated (0.26), which shows that quality stocks are low-beta stocks (i.e. less exposed to market fluctuations).

In what follows, we apply a principal component analysis to our factors.

2.2.2.2 Principal Component Analysis:
In this section, we will split the sample period and study the commonality between the factor return series using Principal Component Analysis (PCA) similarly to Kogan and Tian (2012). Table 14 presents the results of the principal component analysis.

41 - Novy-Marx (2012) The Other Side of Value: The Gross Profitability Premium.

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Table 14: We present the principal component analysis of the different factor return series considered in this study. For all factor returns series, we consider only the US universe and download the data from 1963/09 to 12/2012. The source of the data is defined for each factor in the relevant row. The factors considered are profitability, Quality minus Junk, HML, SMB, momentum, market (minus risk-free), illiquidity, long-term reversal, BAB and short-term reversal. All construction methodologies of factor return series are defined in Table 6.

PC	1963-1991	1991-2012	1963-2012
1	0.38	0.30	0.32
2	0.54	0.561	0.50
3	0.66	0.64	0.63
4	0.75	0.73	0.72
5	0.82	0.81	0.79
6	0.88	0.88	0.86
7	0.93	0.93	0.91
8	0.97	0.97	0.96
9	0.99	0.99	0.99
10	1.00	1.00	1.00

The table presents the PCA of the 10 standard factors which are Quality minus Junk, BAB, HML, SMB, momentum, profitability, market (minus risk-free rate), illiquidity, long-term reversal and short-term reversal. We see that the first three principal components explain roughly 63% of the variance in factor return series. 63% is very comparable to the figures that have been documented by Kogan and Tian (2012) (i.e. 63% from 1971 to 1991 and 69% from 1992 to 2011). In fact, we reach similar a conclusion to the previous authors and find that the factors share a substantial degree of co-movement which is indicated by the amount of the total variance explained by the first few principal components.

In the next section, we study the conditional performance of the factor return series.

2.2.3 Conditional Performance

Asset pricing theory suggests that factors are (positively) rewarded if and only if they perform poorly during bad times, and more than compensate during good times so as to generate a positive excess return on average across all possible market conditions. In technical jargon, the expected excess return on a factor is proportional to the negative of the factor covariance with the pricing kernel, given by marginal utility of consumption for a representative agent (see for example Cochrane (2000) for more details). Hence, if a factor generates an uncertain payoff that is uncorrelated to the pricing kernel, then the factor will earn no reward even though there is uncertainty involved in holding the payoff. On the other hand, if a factor payoff co-varies positively with the pricing kernel, it means that it tends to be high when marginal utility is high, that is when economic agents are relatively poor. Because it serves as a hedge by providing income during bad times, when marginal utility of consumption is high, investors are actually willing to pay a premium for holding this payoff. Standard examples of such rewarded factors in the equity space are the "HML" or "value" factor and "SMB" or "size" factor, which can be regarded as possible proxies for a "distress" factor (Fama and French (1992)). In this exercise, we will test this assumption by considering four states of the world (i.e.

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Worst, Second Worst, Second Best and Best). We compare the average return of all factors for each state of the world to the average market return.

In order for the factors to be "risk" factors, they should pay off poorly in bad states of the world. However, a formal definition of "bad state" of the world is quite hard to reach. Therefore, in this empirical exercise, we use different variables to define the "bad state of the world" and study the factor return in each case.

We consider the following cases:

- Bull/Bear markets: where we rank stock market returns in ascending order. The "Bear" or "Worst" represents the 25 worst performing months and "Bull" or "Best" represents the 25 best performing months.
- Recession/Expansion: where we differentiate between recession and expansion by using the changes in unemployment rate. A positive change in unemployment rate means recession and a negative change in unemployment rate means expansion.
- High/Low Distress Risk: where we differentiate high and low credit risk states by using the changes in the difference between BAA and AAA Moody's corporate yield spreads. A positive change in the credit spread means a high credit risk and negative change in the credit spread means a low credit risk.
- High/Low volatility market: where we differentiate between high and low volatility conditions by using the US VIX Index. A positive change in VIX Index means a high volatility market and negative changes in VIX Index means a low volatility market.
- High/Low interest rate: where we differentiate between high and low interest rate conditions by using the changes in term spread which is the difference between the yields of the 10-year and one-year government bond. A positive change in the term spread means high interest rates and a negative change means low interest rates. A high (low) interest rate market condition could be associated with an expansion (recession) period where the monetary authority would set a high (low) interest rate in order to cool off (boost) the economy.
- High/Low inflation rate: where we differentiate between high and low inflation periods using the changes in CPI index. A positive change in CPI index means high inflation which is considered to be bad news for the economy. A negative change in CPI index means low inflation (or stable prices) which is good news for the economy.
- High/Low industrial production: where we differentiate between high and low industrial production using the industrial production index (IPI). A positive (negative) change in IPI index is associated with an expansion (recession) period.
- Finally, we use the Aruoba-Diebold-Scotti (ADS) Business Conditions Index to differentiate between expansion and recession periods. The ADS business condition index is designed to track real business conditions at high frequency. Its underlying economic indicators (i.e. weekly jobless claims, monthly payroll employment, industrial production, personal income less transfer payments, manufacturing and trade sales, quarterly GDP) blend high and low-frequency information and stock and flow data. A positive ADS value means better than average economic conditions and a negative ADS value means worse than average economic conditions.

The following tables summarise the results. In our interpretation, we only focus on the best and worst performing months.

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Table 15: The table shows the mean returns. We divide our sample in 4 states (Best, Second Best, Second Worst, and Worst). In panel A, we rank stock market returns in ascending order. The "Worst" represents the 25 worst performing months (i.e. ***bear markets****), the "Best" represents the 25 best performing months (i.e.* ***bull markets****), the "Second Best" represents all months with positive returns besides the 25 best performing months, the "Second Worst" represents all months with negative returns besides the 25 worst performing months. In panel B, we rank changes in the unemployment rate in descending order. The "Worst" represents the 25 months with the highest changes in unemployment rate (i.e.* ***recession period****), the "Best" represents the 25 months with the lowest changes in unemployment rate (i.e.* ***expansion period****), the "Second Best" represents all other months (besides the 25 months with the lowest changes in unemployment rate) with low change in unemployment rate, the "Second Worst" represents all other months (besides the 25 months with the highest changes in unemployment rate) with high changes in unemployment rate. In panel C, we rank the credit risk changes in descending order. The credit risk spread is defined by taking the difference between BAA and AAA Moody's corporate yield spreads. The "Worst" represents the 25 months with the highest credit risk changes (i.e.* ***high distress risk****), the "Best" represents the 25 months with the lowest credit risk changes (i.e.* ***low distress risk****), the "Second Best" represents all other months (besides the 25 months with the lowest credit risk changes) with low credit risk changes, the "Second Worst" represents all other months (besides the 25 months with the highest credit risk changes) with high credit risk changes. We also provide the results of the t-stat that the difference between returns (i.e. worst minus best, worst minus second worst or worst minus second best) are zero, thus the bold values are the values where we fail to reject the test that mean returns are equal, the non-bold values are values where we reject the test that the mean returns are equal. For all factor returns series, we consider only the US universe and download the data from 1963/09 to 12/2012. The source of the data is defined for each factor in Table 10. "QMJ" stands for quality minus junk, "Mom" for momentum, "Prof" for profitability, "MKT" for market minus risk-free, "LTR" for long-term reversal, "Liq" for illiquidity factor and "STR" for short-term reversal. All construction methodologies of factor return series are defined in Table 9.*

Panel A	QMJ	Prof	SMB	HML	Mkt	Mom	Liq	LTR	STR	BAB	
Worst	4.07%	0.12%	-2.62%	1.88%	-10.78%	1.92%	-9.10%	0.15%	-1.54%	-0.26%	
Second Worst	**1.60%**	0.16%	**-0.61%**	1.15%	**-3.07%**	0.88%	**-0.94%**	0.38%	**-0.03%**	**1.45%**	
Second Best	**-0.42%**	0.42%	**0.66%**	**0.08%**	**2.72%**	0.76%	**1.22%**	0.29%	**0.88%**	0.78%	
Best	**-2.09%**	1.10%	**1.73%**	**-1.42%**	**9.79%**	**-2.76%**	**-0.15%**	-0.13%	**2.31%**	-1.59%	
Panel B	**QMJ**	**Prof**	**SMB**	**HML**	**Mkt**	**Mom**	**Liq**	**LTR**	**STR**	**BAB**	**Unemployment**
Worst	0.55%	0.25%	1.28%	-0.30%	-0.67%	-0.61%	-1.83%	0.55%	1.60%	-0.14%	7.58%
Second Worst	0.25%	0.21%	-0.02%	0.58%	0.46%	0.52%	-0.14%	0.27%	0.18%	0.71%	2.27%
Second Best	0.47%	0.46%	0.16%	0.37%	0.59%	0.92%	0.18%	0.29%	0.65%	1.00%	-1.35%
Best	0.37%	-0.03%	-0.11%	1.42%	-0.18%	0.53%	0.16%	0.42%	0.44%	1.32%	-5.48%
Panel C	**QMJ**	**Prof**	**SMB**	**HML**	**Mkt**	**Mom**	**Liq**	**LTR**	**STR**	**BAB**	**Credit Spread**
Worst	1.37%	-0.30%	-0.76%	-0.20%	-0.80%	-0.47%	0.58%	0.63%	0.38%	0.25%	26.54%
Second Worst	0.66%	0.63%	-0.21%	0.58%	0.41%	0.67%	-0.16%	0.03%	0.48%	0.66%	6.54%
Second Best	0.21%	0.26%	0.39%	0.41%	0.56%	0.80%	0.15%	0.43%	0.60%	1.02%	-3.76%
Best	-0.26%	-0.22%	0.32%	0.76%	0.72%	0.84%	-1.68%	0.42%	-0.09%	1.09%	-17.41%

The first Table (Table 15) considers bull/bear market conditions, high/low changes in unemployment rate and high/low changes in distress risk.

Panel A shows that the market column (i.e. MKT) is ranked in ascending order where in the worst (best) market we have average returns of -10.38% (9.79%). Surprisingly, not all factors underperform (outperform) in worst (good) market conditions. For instance while the SMB factor shows negative performance of -2.62% in the worst state of the world, HML, momentum and quality (QMJ) factors show positive returns of 1.88%, 1.92% and 4.07% respectively. Panel B shows the state of world ranked using the changes in unemployment rate. We observe that market performance is negative in both the worst and best state of the world which may imply that the relation or the correlation between unemployment rate and the market performance is weak, which also may make it difficult to interpret the performance of other factors with respect

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to the market factor. Surprisingly, only the BAB factor performance seems to increase as we move from the worst to the best state of the world. Finally, panel C indicates that the link between the market performance and credit spread changes is significant with the market showing an underperformance (over-performance) of -0.80% (0.72%) in worst (bad) states of the world. Similar observations could be made for SMB, HML, momentum and BAB. It is interesting here to underline the link between distress risk and the SMB factor, which is largely documented in the literature.

The following Table (Table 16) considers high/low volatility, high/low term spread[42] changes and high/low inflation changes.

Panel D provides evidence that the market performance decreases as the volatility changes increase. However, QMJ and BAB seem to be negatively correlated with

42 - Many studies attribute the ability of the term spread to forecast economic activity to actions by monetary authorities to stabilise output growth. For example, monetary policy tightening causes both short and long term interest rates to rise. Laurent (1988, 1989) argues that the yield curve reflects the monetary policy stance and finds that the term spread predicts changes in the growth rate of real GDP.

Table 16: The table shows the mean returns. We divide our sample in 4 states (Best, Second Best, Second Worst, and Worst). In panel D, we rank the changes in US VIX Index in descending order. The "Worst" represents the 25 months with the highest volatility changes (i.e. ***high volatility****), the "Best" represents the 25 months with the lowest volatility changes (i.e.* ***low volatility****), the "Second Best" represents all other months (besides the 25 months with the lowest volatility changes) with low volatility changes, the "Second Worst" represents all other months (besides the 25 months with the highest volatility changes) with high volatility changes. In panel E, we rank the changes in term spread in ascending order where the term spread is the difference between the yields of the 10 year and one year government bond. The "Worst" represents the 25 months with the lowest term spread changes (i.e.* ***low term spread period****), the "Best" represents the 25 months with the highest term spread changes (i.e.* ***high term spread period****), the "Second Best" represents all other months (besides the 25 months with the highest term spread changes) with high term spread changes, the "Second Worst" represents all other months (besides the 25 months with the lowest term spread changes) with low term spread changes. In panel F, we rank the changes in inflation rate in descending order. The "Worst" represents the 25 months with the highest inflation changes (i.e.* ***high inflation period****), the "Best" represents the 25 months with the lowest inflation changes (i.e.* ***low inflation period****), the "Second Best" represents all other months (besides the 25 months with the lowest inflation changes) with low inflation changes, the "Second Worst" represents all other months (besides the 25 months with the highest inflation changes) with high inflation changes. We also provide the results of the t-stat that the difference between returns (i.e. worst minus best, worst minus second worst or worst minus second best) are zero, thus the bold values are the values where we fail to reject the test that mean returns are equal, the non-bold values are values where we reject the test that the mean returns are equal. For all factor returns series, we consider only the US universe and download the data from 1963/09 to 12/2012. The source of the data is defined for each factor in Table 10. "QMJ" stands for quality minus junk, "Mom" for momentum, "Prof" for profitability, "MKT" for market minus risk-free, "LTR" for long-term reversal, "Liq" for illiquidity factor and "STR" for short-term reversal. All construction methodologies of factor return series are defined in Table 9.*

Panel D	QMJ	Prof	SMB	HML	Mkt	Mom	Liq	LTR	STR	BAB	Change in Vol
Worst	4.02%	1.40%	-1.79%	1.17%	-6.78%	3.30%	-3.83%	1.02%	-2.31%	1.80%	8.51%
Second Worst	**1.62%**	0.82%	**0.58%**	0.48%	**-2.65%**	**0.20%**	**-0.04%**	0.41%	**0.30%**	2.41%	3.51%
Second Best	**0.04%**	**0.39%**	**0.08%**	0.43%	**1.46%**	**0.88%**	**0.77%**	0.25%	**0.33%**	0.90%	-0.72%
Best	**-1.26%**	0.11%	**0.05%**	-0.54%	**4.72%**	**-3.89%**	**0.78%**	0.09%	**1.78%**	**-2.88%**	-7.40%
Panel E	**QMJ**	**Prof**	**SMB**	**HML**	**Mkt**	**Mom**	**Liq**	**LTR**	**STR**	**BAB**	**Change in IR**
Worst	0.86%	1.06%	0.08%	-0.75%	-1.01%	1/32%	-2.09%	0.13%	0.90%	-0.65%	-68.28%
Second Worst	0.62%	0.51%	-0.16%	**0.50%**	0.28%	1.25%	-0.15%	0.25%	0.14%	**0.94%**	-16.73%
Second Best	0.28%	0.19%	0.25%	**0.51%**	0.50%	0.48%	0.23%	0.30%	0.52%	**0.95%**	9.76%
Best	-0.28%	0.42%	1.02%	0.62%	**2.87%**	-1.40%	-0.29%	1.00%	3.22%	0.68%	76.60%
Panel F	**QMJ**	**Prof**	**SMB**	**HML**	**Mkt**	**Mom**	**Liq**	**LTR**	**STR**	**BAB**	**Change in inflation**
Worst	0.00%	-1.30%	0.31%	0.38%	-1.73%	2.31%	-1.22%	0.12%	0.04%	-0.60%	1.17%
Second Worst	0.44%	**0.15%**	-0.08%	0.73%	0.14%	0.96%	-0.33%	0.23%	0.52%	**1.11%**	0.57%
Second Best	0.45%	**0.49%**	0.05%	0.34%	**0.77%**	**0.45%**	0.15%	0.37%	0.58%	**1.04%**	0.19%
Best	1.02%	**1.48%**	0.79%	0.08%	1.22%	-0.73%	0.27%	0.30%	0.24%	0.27%	-0.34%

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volatility changes, which is in line with what we would expect as these factors are long high quality and defensive stocks. Panel E indicates that the increase (decrease) in term spread changes result in underperformance (over-performance) of -0.75% (0.62%) for the HML factor. This result seems to be consistent with the findings of Petkova (2006) that highlights the possible link between interest rate risk and the HML factor. The performance of LTR and MKT show also a strong relation with interest rate changes. Finally, Panel F ranks the factors according to changes in inflation rate. Here again we observe that the market performance collapses to -1.73% when inflation changes are high. Surprisingly, profitability and QMJ factors are also related to the inflation rate as they show poor (good) performance in a state of high (low) inflation.

Finally, Table 17 considers high/low changes in the industrial production index and high/low Aruoba-Diebold-Scotti (ADS) Business Conditions Index, which is another measure of macro risk downloaded from the central bank of Philadelphia.

On the one hand, panel G underlines the weak link between the changes in IPI and the market performance. On the other hand, in panel H we observe that as the ADS value increases the market and BAB performances increase. Furthermore, the HML factor also shows a strong link with the ADS index values.

Our findings reveal that, across all variables used to do the sorting (i.e. market, unemployment rate, inflation rate, ADS business index, VIX, IPI, term spread and credit spread) none of the factors

Table 17: The table shows the mean returns. We divide our sample in 4 states (Best, Second Best, Second Worst, and Worst). In panel G, we rank the changes in industrial production index (IPI) in ascending order. The "Worst" represents the 25 months with the lowest IPI changes (i.e. ***low IPI****), the "Best" represents the 25 months with the highest IPI changes (i.e.* ***low IPI****), the "Second Best" represents all other months (besides the 25 months with the highest IPI changes) with high IPI changes, the "Second Worst" represents all other months (besides the 25 months with the lowest IPI changes) with low IPI changes. In panel H, we rank the Aruoba-Diebold-Scotti (ADS) Business Conditions Index in ascending order. The "Worst" represents the 25 months with the lowest ADS (i.e.* ***recession****), the "Best" represents the 25 months with the highest ADS (i.e.* ***expansion****), the "Second Best" represents all other months (besides the 25 months with the highest ADS) with high ADS, the "Second Worst" represents all other months (besides the 25 months with the lowest ADS) with low ADS. We also provide the results of the t-stat that the difference between returns (i.e. worst minus best, worst minus second worst or worst minus second best) are zero, thus the bold values are the values where we fail to reject the test that mean returns are equal, the non-bold values are values where we reject the test that the mean returns are equal. For all factor returns series, we consider only the US universe and download the data from 1963/09 to 12/2012. The source of the data is defined for each factor in Table 10. "QMJ" stands for quality minus junk, "Mom" for momentum, "Prof" for profitability, "MKT" for market minus risk-free, "LTR" for long-term reversal, "Liq" for illiquidity factor and "STR" for short-term reversal. All construction methodologies of factor return series are defined in Table 9.*

Panel G	QMJ	Prof	SMB	HML	Mkt	Mom	Liq	LTR	STR	BAB	Change in Vol
Worst	0.76%	0.83%	0.91%	0.38%	0.06%	-0.44%	-1.52%	0.70%	1.54%	0.23%	-1.88%
Second Worst	0.50%	0.45%	0.11%	0.54%	0.53%	0.80%	-0.43%	0.28%	0.76%	0.90%	-0.29%
Second Best	0.28%	0.26%	0.09%	0.39%	0.53%	0.70%	0.46%	0.29%	0.34%	0.88%	00.57%
Best	0.73%	0.09%	0.19%	0.79%	-0.70%	1.04ù	-1.57%	0.30%	0.01%	1.10%	1.79%
Panel H	**QMJ**	**Prof**	**SMB**	**HML**	**Mkt**	**Mom**	**Liq**	**LTR**	**STR**	**BAB**	**Change in IR**
Worst	1.30%	1.40%	0.44%	-0.86%	0.02%	-1.98%	-2.22%	0.05%	1.42%	-0.86%	-2.72
Second Worst	0.35%	0.46%	0.33%	**0.55%**	0.38%	**1.05%**	-0.29%	0.36%	0.41%	**0.90%**	-0.58
Second Best	0.38%	**0.23%**	-0.03%	**0.46%**	0.43%	**0.70%**	**0.25%**	0.28%	0.50%	**0.93%**	0.39
Best	0.07%	**-0.12%**	0.51%	1.05ù	1.94%	0.65%	0.72%	0.35%	0.80%	**1.50%**	1.60

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consistently perform poorly in bad states of the world and more than compensate in good market conditions. In fact, the tables above show that the results on the factor performances change depending on the variable used to name the bad/good state of the world. Overall, we believe these results are in line with the mixed interpretation on the economic rationale behind the equity risk factors as there is no clear answer as to whether the factors are compensation for systematic risk or the results of behavioural anomalies.

2.3 Constructing Factor-Mimicking Portfolios

The factors discussed in Section 2.2 all correspond to portfolios of tradable assets. Many such factors are not directly tradable because investors face implementation problems related to shorting, transaction costs, tax issues or liquidity, which may be detrimental to the profitability of such factor strategies. In such cases, empirical research resorts to the construction of factor-mimicking portfolios which not only use alternative methods of weighting (e.g. signal sorting, long-only etc.) but also are more realistic in their implementation method as they take into account several constraints related to leverage for the case of long/short portfolios, control of non-desired factor exposures, sector neutrality or transaction costs.

In what follows, we provide a brief outline of the construction principles of such factor-mimicking portfolios.

2.3.1 Long/short versus Long- Only Portfolio Construction

We provide here a discussion of whether risk premia can be efficiently captured in long-only portfolios or whether they require long/short portfolios.

Israel and Moskowitz (2013) find that long-only portfolios capture most of the profitability of the size and value and about half of the potential profitability of momentum strategies compared to long/short strategies. They document that long-only portfolios that capture the relevant factor obtain average returns that are significantly different from what can be attributed to market exposure only. Blitz, Huij, Lansdorp and van Vliet (2014) empirically compare long-only versus long/short approaches to factor investing in order to determine which approach is preferable under various conditions. They find that although the long/short approach is superior in theory, the long-only approach seems to be a better alternative in most scenarios that account for practical issues such as benchmark restrictions, implementation costs and factor decay. However, Stambaugh, Yu and Yuan (2012) provide evidence that the short side of the equity factor portfolio is particularly profitable following times of high investor sentiment, suggesting that leaving out the short side means investors forego some of the rewards of long/short factor investing when following long-only approaches in such market conditions.

2.3.2 Sorting versus Weighting

We discuss here some examples of how score-based weighting schemes or other weighting schemes can be of use in addition to simple sorting procedures. For example, Asness, Moskowitz and Pedersen (2013) propose signal-weighted factor portfolios for value and momentum where they rank stocks based on the ranking of their signal. The authors construct value and momentum factors for each asset class (i.e. equities, bonds, commodities and currencies), which are zero-cost long/short portfolios that use

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the entire cross-section of securities within each asset class. For any security with a signal (either value or momentum), they weight the securities in proportion to their cross-sectional rank, obtained as the signal minus the cross-sectional average rank of that signal. According to the authors, the use of the signal ranks as portfolio weights allows them to reduce the influence of outliers.

In another study, Novy-Marx (2013) creates price and quality signals for each stock in order to combine value and quality metrics in a single strategy which puts half of its weighs on valuations and the other half on a combination of quality criteria. On the one hand, a stock price signal is computed by taking the average of a firm's book-to-price and earnings-to-price ranks among all stocks. On the other hand, a stock quality signal is based on several quality metrics. Among the quality metrics discussed, the author presents the Graham (or "G") Score, which takes into account several key quality criteria. For instance, a "firm's G-score gets one point if a firm's current ratio exceeds two, one point if net current assets exceeds long-term debt, one point if it has a ten-year history of positive earnings, one point if it has a ten-year history of returning cash to shareholders, and one point if its earnings per share are at least a third higher than they were ten years ago." As a result, firms obtain a quality score from zero to five, the highest scores being attributed to the highest quality firms.

2.3.3 Controlling Exposure to Multiple Factors

This section discusses the benefits and issues of approaches that aim at obtaining a pure factor exposure to a given factor while neutralising exposure to other factors. In particular, we discuss i) double, triple or quadruple sorting approaches and ii) constraints to avoid unintended factor exposures.

Fama and French (2014) propose an extended version of their three-factor model (1993), with two additional factors, namely profitability and investment, to complement the market, size and book-to-market (or value) factors. The authors argue that disentangling value, investment and profitability is not an easy task as these characteristics are correlated[43]. According to Fama and French (2014), high B/M value stocks tend to have low profitability and investment, and low B/M growth stocks tend to have high profitability and to take more risk to generate profit. Because of this correlation, the authors mention that double-sorted (i.e. size-B/M, size-profitability, and size-investment) portfolios do not isolate value, profitability, and investment effects in average returns. Therefore, to reduce such dependence, Fama and French (2014) form triple-sorted portfolios where they sort jointly on size, B/M, profitability ("OP"), and investment ("Inv"). They form two size groups (small and big), using the median market cap for NYSE stocks as the breakpoint, and use NYSE quartiles to form four groups for each of the other two sort variables (2x4x4 sorts). As a final alternative, Fama and French (2014) also utilise four sorts to control jointly for size, B/M, OP, and Inv. They sort stocks independently into two size groups, two B/M groups, two OP groups, and two Inv groups using NYSE medians as breakpoints (2x2x2x2 sorts). Thus, each specific factor is roughly neutral with respect to the other three factors. The authors underline that four variables may be the most one can control at the same time. They suggest that the use of momentum factor in addition, may

43 - The problem of correlation is also inherent in the original Fama and French (1993) three factor model.

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introduce correlations between factors, due to a lack of diversification in portfolios used to construct factors.

In a recent study, Melas, Suryanarayanan and Cavaglia (2010) propose an optimisation replication method which constructs portfolios that have maximum exposure to a target factor, zero exposure to all other factors and minimise portfolio risk. The method proposed is flexible enough to include investability constraints which may come from regulatory requirements that impose limits on leverage of the long/short factor-replicating portfolio. The authors show that the value and momentum portfolio can be efficiently replicated with the suggested methodology.

2.3.4 Sector Neutrality and Within-Industry versus Across-Industry Effects

A key issue with many of the factor portfolios mentioned above is to see whether the reward to a factor depends mainly on industry effects (i.e. the factor returns capture return differences across industries) or mainly on stock level effects within industries. We review the evidence for (i) value (see e.g. Novy-Marx 2011), (ii) low risk (see Asness, Frazzini and Pedersen 2013), and (iii) momentum factors (Moskowitz and Grinblatt 1999).

Novy-Marx (2011) studies the industry effect in the value factor. He finds different results whether the test is made across industries or within industries. The relation between expected returns and book-to-market across industries is weak and non-monotonic, while the relation between expected returns and book-to-market within industries is strong and monotonic. It is concluded that the value premium is mainly an intra-industry phenomenon. In particular, the author shows that if firms are sorted on the basis of the intra-industry book-to-market, significant variations in returns are obtained, which is explained by the three-factor model. Alternatively, firms are sorted on the basis of the industry book-to-market, no significant variation in returns is obtained.

As far as the low-risk factor is concerned, Asness, Frazzini and Pedersen (2013) show that low-risk investing works both for selecting stocks within an industry and for selecting industries. The authors stress that the risk-adjusted returns are even stronger within industry. Furthermore, the industry-neutral Betting against Beta (BAB) (i.e. factors that invest long in a portfolio of low-beta stocks while short-selling a portfolio of high-beta stocks) has delivered positive returns in each of the 49 US industries and in 61 of 70 global industries. In fact, the regular BAB factor is more dependent on the industry-neutral stock selection than on industry selection. All this empirical evidence on BAB and low-risk investing in general disproves the idea that such strategies are industry bets.

Although the industry effect has been rejected for the low-risk factor, the same cannot be said for the momentum factor. In fact, Moskowitz and Grinblatt (1999) explore various explanations behind the persistence of the positive returns in momentum strategies. They find that industry momentum is the source of most of the momentum trading profits over intermediate investment horizons (i.e. 6 to 12 months). In particular, the authors find that profitability of individual stock momentum strategies is mainly explained by the significant profits generated by that persistence in industry return components.

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2.3.5 Managing Transaction Cost and Tax Effects of Dynamic Factor Strategies

A key difference of any factor approach with standard market-cap-weighted reference indices is that the implementation of the factor tilt requires potentially substantial rebalancing or dynamic trading. For example, a factor portfolio that is based on sorting stocks by their price to book ratio will incur trading activity as stock valuation changes over time and hence stocks shift from high price-to-book to low price-to-book and vice versa. We discuss here how robust factor premia are to transaction costs and tax effects. For momentum in particular, several papers suggest that many momentum trading rules are not only unprofitable when realistic transaction costs are taken into account but also limited in capacity.

On the one hand, Lesmond, Schilb and Zhou (2004) find that relative strength strategies (or momentum strategies) require high turnover and thus heavy trading among costly stocks. The authors provide evidence that high trading costs are associated with stocks that generate momentum returns, which implies that the trading profit opportunities observed in stocks vanish. On the other hand, Korajczyk and Sadka (2003) investigate the effect of trading costs on the profitability of momentum strategies. In particular, the authors have determined that a momentum-based fund could achieve a size from $4.5 billion to over $5.0 billion (relative to market capitalisation in December 1999) before its abnormal returns became either statistically insignificant or driven to zero. In the same way, Korajczyk and Sadka (2003) conclude that abnormal returns are not driven to zero until the investment size reaches $5.0 billion. However, these authors consider that momentum-based strategies remain exploitable while its amount under investment stays lower than $1.5 billion.

Furthermore, several authors argue that after-tax returns of investments are the critical input into the asset allocation decision. Therefore, taxation is an important element to take into consideration when analysing the profitability of equity style portfolios. To this end, Israel and Moskowitz (2012) investigate the tax efficiency and after-tax performance of long-only equity styles. After accounting for tax, the authors show that value and momentum (growth) portfolios outperform (underperform) the market. Furthermore, they find that because the momentum portfolio results in short-term losses it tends to be more tax efficient than Value strategies, despite the high turnover that is inherent in momentum style investment.

After presenting different aspects of the implementation of equity style portfolios, we provide in the next section an overview of factor indices available in the industry as well as their construction methodology.

2.4 Factor Index Industry Landscape: An Overview of Methodologies

This section provides a brief overview of equity index offerings from major index providers. The offerings in the industry can be broadly categorised into (i) fundamentally-weighted indices, (ii) hedge fund replication indices which rely on three approaches (i.e. mechanical, distributional and factor-based methods) and (iii) factor indices which are classified into single and multiple factor indices. For each index category, we aim to provide a

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conceptual description, examples of some of the key index players, and criticism (e.g., data mining, robustness, hidden factor exposure, difficulty of replicating the factor exposure, etc.) that is typically associated with such indices.

2.4.1 Fundamentally-Weighted Indices

A fundamentally-weighted index is constructed by calculating the economic size (or "footprint") of each company within the index's universe, based on such factors as: revenues; cash flow; book value; and dividends. The index is then weighted to reflect the relative economic size of each stock to the overall universe. Since such indices are not weighted by market prices they are not influenced by short-term market changes. Moreover, since the weighting is based on sales, book value and other measures of economic size that change slowly, the index can be managed through ETFs or mutual funds on a relatively tax efficient basis.

Fundamentally-weighted indices were of course not meant as factor indices when they were developed and launched as a product. In fact, the original publications were mostly silent about the underlying factor tilts of these indices. Instead, such indices were launched as improvements of the economic representativity relative to cap-weighted indices by weighting stocks by their "economic footprint". However, when the factor tilts of such indices became widely documented and factor investing became fashionable, providers changed their positioning of such indices as factor-tilted indices. Amenc, Goltz, Lodh, and Sivasubramanian (2014) however provide evidence that the stock selection criteria used by such indices (i.e. the "economic size" measures such as cash flows, earnings, dividends etc.) are not associated with statistically significant risk premia. Significant risk premia however exist for valuation ratios, which put such fundamental size metrics in relation to the stock price. Therefore, such fundamentals-based indices cannot be classified as factor indices properly speaking. However, we have included fundamentally-weighted strategies in our questionnaire due to their popularity and the positioning by providers as factor-tilted indices.

Below, we present some examples of fundamentally-weighted indices available in the industry, as defined on valueweightedindex.com:

- **FTSE RAFI US 1000:**
"The index selects the largest U.S. stocks (based on economic size) and weights these stocks on their economic size. For this index, economic size is measured by a company's five-year average of book value, cash flow, dividends, and sales. Price and value criteria are not included in this index."
- **WisdomTree Total Dividend:**
The index "measures the performance of U.S. companies that pay regular cash dividends on shares of their common stock and that meet specified requirements as of the index measurement date. Companies are weighted in the Index based on their projected cash dividends as of the Index measurement date. The Index includes all large-capitalisation, mid-capitalisation and small-capitalisation securities that meet the Index requirements and is, in this sense, a total market index for the dividend-paying segment of the U.S. market."
- **WisdomTree Large Cap Value:**
"The WisdomTree LargeCap Value Index is a fundamentally-weighted index that measures the performance of large -cap value companies. The WisdomTree LargeCap Value Index consists of U.S.

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companies that have positive cumulative earnings over the past four fiscal quarters and that meet the Index's market capitalisation, liquidity, and other requirements as of the Index measurement date. For these purposes, "earnings" are determined using a company's reported net income, excluding special items, applicable to common shareholders. WisdomTree Investments creates a "value" score for each company based on the company's Price to Earnings Ratio, Price-to-Sales Ratio, Price-to-Book Value and 1-year change in stock price. The top 30% of companies with the highest value scores within the 1,000 largest companies by market capitalisation are included in the WisdomTree LargeCap Value Index. Companies are weighted in the WisdomTree LargeCap Value Index annually based on earnings."

- **WisdomTree Total Earnings:**

"The WisdomTree Earnings Index is a fundamentally-weighted index that measures the performance of earnings-generating companies within the broad U.S. stock market. Companies are weighted in the Index based on their earnings over their most recent four fiscal quarters preceding the Index measurement date. For these purposes, "earnings" are determined using a company's "Core Earnings." Core Earnings is a standardised calculation of earnings developed by Standard & Poor's that is designed to include expenses, incomes and activities that reflect the actual profitability of a company's ongoing operations. The Index includes large-capitalisation, mid-capitalisation and small-capitalisation securities and is, in this sense, an earnings-weighted index for the total U.S. market."

- **FTSE RAFI Developed Markets ex-US:**

"Companies in the index are selected and weighted based on the following four fundamental measures of firm size: book value, cash flow, sales and dividends. Price and value criteria are not included in this index. The index selects from approximately 1,000 securities of companies with market capitalisations of between approximately $200 million and $200 billion that were domiciled in Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Israel, Italy, Japan, Luxembourg, the Netherlands, New Zealand, Norway, Portugal, Singapore, South Korea, Spain, Sweden, Switzerland, Thailand and the United Kingdom or primarily listed on an exchange in such countries. The Fund generally invests in all of the securities comprising its Underlying Index in proportion to their weightings in the Underlying Index."

However, there has been strong criticism of fundamental indexing as it is argued that such indices are only an alternative way to introduce a value bias into a portfolio. Value-tilted portfolios have historically outperformed unbiased portfolios so it is not a surprise that a fundamentally-weighted index outperforms the cap-weighted index in a long-term period. In his paper, Kaplan (2008) concludes that fundamental indexing "contains a value bias and does not depend on circumstances (i.e. on the observed values of variables). It is always true." This result implies that fundamental weighting is neither a revolutionary paradigm nor a new investment based on financial theory, it is merely a value tilt introduced in a portfolio.

Several conditions are necessary in order for fundamentally-weighted indices outperform the common benchmark. First, the valuations errors that produced the superior returns of fundamentally-weighted indices in the past must still

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be observed in the future. The market should integrate the fact that overvalued stocks may revert to the mean rather than remain overvalued. Both assumptions may lack robustness over time as the valuation errors could be sample dependent.

Our description above shows that, although not marketed by index providers as such, fundamentally-weighted indices are nothing more than a hidden replication of Value strategies. Other types of indices (i.e., hedge fund indices) claim to explicitly replicate hedge fund strategies through risk factor-based replication. However, as explained below, such replication suffers from numerous drawbacks that will be highlighted in the following section.

2.4.2 Hedge Fund Replication Strategies

This section describes the three main approaches to hedge fund replication. We then focus on the factor-based approach which is the most popular in the industry. Hedge replication strategies are categorised in three ways: mechanical, distributional and factor-based (see Freed (2013) for a review of hedge fund replication strategies). Each replication strategy method is due to replicate the behaviour of groups of hedge fund managers with only a partial knowledge of their true behaviour. The mechanical approach reproduces actual positions of hedge fund managers. The distributional approach replicates the exposure of hedge fund portfolios using the statistical properties of the time series of hedge returns. Finally, the factor-based approach uses the correlation between hedge fund indices and conventional investment indices (i.e. ETFs, government bonds, futures, etc.).

- **Mechanical approach:**
Managers generate portfolios with positions that are typical of particular hedge fund strategies in order to replicate such strategies' returns. That is the reason why this method is sometimes referred to as "trade-related method". Only a small portion of the market adopts this method.

- **Distributional approach:**
This method utilises portfolios of future contracts in order to mimic the statistical properties of the targeted hedge fund strategy. This approach is mathematically satisfying. However, it lacks commercial success, mainly because it does not provide superior results compared to a direct investment in a portfolio of hedge funds.

- **Factor-based approach:**
In this approach, a linear factor replication identifies risk factors that explain or drive the return of the hedge fund strategy. The model selects the factors that have the highest explanatory powers for the hedge fund index returns corresponding to the strategy. The regression decomposes index returns into a random and non-random (or systematic return) component by computing the exposure (or beta) of index returns to risk factors that serve as explanatory variables. Factor-based replication serves to reproduce hedge fund beta using portfolios of investable proxies for the regression.[44]

Below, we present some examples of hedge fund indices available in the industry:

- **FTSE Hedge Index:**
The index is "an investable index that reflects the aggregate risk and return characteristics of the open, investable hedge fund universe" (see www.rimes.com).

44 - The factor-based approach can only seek to replicate the non-random part, which is the hedge fund betas, and cannot reproduce the random part.

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- **FTSE Hedge Momentum Index:**
The index is an investment strategy designed to outperform the FTSE Hedge index. This is achieved by over or underweighting funds according to whether or not they demonstrate persistent positive returns (moment). According to FTSE's website, the hedge fund momentum index has returned a 10.1% annualised performance, representing a 3.9% outperformance over and above the FTSE Hedge index.

- **Barclays Hedge Fund Index:**
The index "is a measure of the average return of all hedge funds (excepting funds of funds) in the Barclays database. The index is simply the arithmetic average of the net return of all funds that have reported that month. The index is recalculated and updated real-time as soon as the monthly returns for the underlying funds are recorded. Only funds that provide net returns are included in the index calculation." (see www.barclayshedge.com)

- **Morningstar Hedge Fund Index:**
The index captures the performance of the most investable portion of the hedge fund industry and represents hedge funds using a wide variety of trading strategies.

While the factor-based approach has proven to be popular among practitioners, such a method suffers from numerous drawbacks. Indeed, Freed (2013) argues that the success of factor-based strategies relies on the magnitude of the hedge fund index beta signal, as well as the serial correlation of the index itself. In addition, it also depends of the tradability of the risk factors. These points will be discussed below:

The regression of the time series of hedge returns attributes 100% of the returns to alpha, beta and errors, but a factor-based strategy can only replicate the part classified as hedge fund beta. As a result, the part of the R^2 related to hedge fund beta gives only an indication of the ex-ante performance or how successful the replication strategy may be. Moreover, in order for the replication strategy to be successful, replicators need to be made of hedge fund indices exposed to similar risk factors than the index they seek to replicate. The choice of such a fund determines the strength of the risk factor sensitivities a replicator seek to capture. The assignment of funds to a replication strategy becomes cumbersome when one encounters funds whose investments span two or three related strategies. For example, some long/short equity funds have a lot in common with event-driven strategies. Such redundancy may mask risk factor sensitivities which in turn imply that an index made of funds that are not exposed to similar risk factors cannot result in a satisfying replication strategy.

Serial correlation matters in the factor-based method as the success of the replication occurs only when the future resembles the past. Indeed, if the past performance of hedge fund index is a good predictor of its future performance, then using hedge fund index past performance to replicate the index may be a good strategy. Furthermore, a successful replication methodology depends on how tradable the risk factors are, as a replicator needs access to tradable proxies for the risk factors that drive the returns of a particular index. While some risk factors may be traded relatively easily through ETFs and futures contracts (e.g., equity indices, commodities and interest rates), others may be more difficult to trade because of lack of transparency and liquidity (e.g., exposure to credit risk).

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Overall, Freed (2013) argues that only "some hedge fund replication strategies produce indices with strong beta signals and serial correlation", as described above. Moreover, hedge fund strategies also differ in the level of turnover in the assets held by the funds and the number of trading strategies their managers intend to implement. These constraints further limit the scope of the applicability of the factor replication method as strategies with high turnover and high numbers of trading strategies tend to produce less robust risk factor correlations than strategies with low turnover and fewer trading strategies.

As discussed above, hedge fund indices provide indirect and incomplete exposure to risk factors through inefficient risk factor replication. This inefficiency leads to the questioning of the validity of replication methods which clearly lack robustness. Kogan and Tian (2012) quantify how easy it is to generate "seemingly successful empirical factor models" and show that the ease of construction of factor models and of the "freedom in selecting test assets" (through data mining) present a serious concern in empirical asset pricing.

In the coming section, we focus on strategies that provide explicit exposure to such risk factors.

2.4.3 Factor Indices

This section provides a brief overview of equity factor index offerings from major index providers. The factor indices are classified into single-factor indices, which aim at providing explicit exposure to a common risk factor, and multi-factor indices, which provide a global portfolio which allocates to several risk premia. In what follows, we provide a summary description of the index methodology as well as the implementation choices.

Due to the predominance of long-only indices in practical application, we focus here on long-only indices and do not include long/short index offerings.

- Single-Factor Indices

To get a synthetic view of the different single-factor indices, we have selected one index each from the following index providers: ERI Scientific Beta, MSCI, Russell, and S&P. We consider indices for each of four main factors, namely the Low Volatility, Momentum, Size and Value factors.

Russell offers a so-called High Efficiency Factor Index series which provides indices for the Low Volatility, Momentum and Value factors. These indices seek to tilt the portfolio based on factor scores taking market cap weights as a starting point. For the mid-cap factor, Russell publishe a Russell US Mid-Cap Index which selects stocks in the relevant size range and market cap weights them.

ERI Scientific Beta publishes multi-strategy indices for these four factors, where each factor index is based on a stock selection of 50% of stocks in the universe and then uses a diversification-based weighting scheme to weight stocks. In particular, the indices use a Diversified Multi-Strategy weighting which consists of an equal allocation to the five following weighting schemes: Maximum Deconcentration, Risk Weighted, Maximum Decorrelation, Minimum Volatility and Maximum Sharpe Ratio.

MSCI offers the MSCI USA Momentum index, which selects stocks by momentum

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Table 19 – Construction methodology of factor indices of various providers

Factor	Index	Stock Selection	Weighting Scheme	Risk Controls
Scientific Beta Index Methodology				
Size	SciBeta Div. Multi-Strategy Mid-Cap Index	Half the stocks by relevant score	Same weighting scheme for selected stocks (Diversified Multi-Strategy by default)	Cap on multiple of market cap and weight of individual securities
Value	SciBeta Div. Multi-Strategy Value Index			
Mom.	SciBeta Div. Multi-Strategy High Momentum Index			
Low Vol.	SciBeta Div. Multi-Strategy Low Volatility Index			
Russell Index Methodology				
Size	Russell Mid-Cap Index	Smallest 800 companies from parent index	Cap-Weighted	None
Value	Russell High Efficiency Value	Scoring based on Non-Linear Probability method, results in approximately 50% of the stocks of the CW parent index	Conversion of the scores calculated in the stock selection stage into active weights by using the NLP method using cap weights as base	Turnover minimisation by calculating new stocks' weights using a banding process
Mom.	Russell High Efficiency Momentum	Scoring based on Non-Linear Probability method, results in approximately 50% of the stocks of the CW parent index		
Low Vol	Russell High Efficiency Low Vol	Scoring based on Non-Linear Probability method, results in approximately 30% of the stocks of the CW parent index		
FTSE Index Methodology				
Size	FTSE Developed Size Factor	Selection based on size factor exposure score	Using cap weights as base, stocks weights are tilted by their respective factor scores	Country and industry constraints
Value	FTSE Developed Value Factor	Selection based on value factor exposure score		
Mom.	FTSE Developed Momentum Factor	All stocks in CW parent index universe		
Low Vol.	FTSE Developed Volatility Factor	Selection based on volatility factor exposure score		
MSCI Index Methodology				
Size	MSCI Equal-Weight Index	All stocks in CW parent index universe	Equal-weighted	None
Value	MSCI Value-weighted index	All stocks in CW parent index universe	Score adjusted by investability factor	None
Mom.	MSCI Momentum Index	Selection by momentum score (fixed number of constituents to target 30% market cap coverage)	Market cap* momentum score	Cap on weight of individual security
Low Vol.	MSCI Minimum Volatility Index	All stocks in CW parent index universe	Optimisation to minimise portfolio risk	Sector and country weight constraints Cap on multiple of market cap of individual security

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S&P Index Methodology				
Size	S&P Mid-Cap 400 Index	Companies with unadjusted market cap of USD 1.4 billion to USD 5.9 billion	Cap-Weighted	Liquidity constraint
	S&P Mid-Cap 400 Equal Weight Index	Companies with unadjusted market cap of USD 1.4 billion to USD 5.9 billion	Equal-weighted	Liquidity constraint
Value	S&P 500 Value Index	Selection based on the relationship between value and growth scores, results in approximately 50% market cap coverage of the parent index	Cap-Weighted	None
	S&P 500 Pure Value Index	Selection based on the relationship between value and growth scores, results in approximately 25% market cap coverage of the parent index	Score Weighted	Capping of scores to avoid overconcentration
Mom.	S&P 1500 Positive Momentum Tilt	All stocks in CW parent index universe	Modified market cap weighting scheme	None
Low Vol.	S&P 500 Low Volatility Index	100 least volatile stocks from parent index	Inverse Volatility	None
	S&P 500 Minimum Volatility Index	Based on optimisation	Optimisation to minimise forecasted portfolio volatility	Cap stock and sector weights. Constraints on risk factor exposures
	S&P 1500 Reduced Volatility Tilt Index	All stocks in CW parent index universe	Modified market cap weighting scheme	None

score and weights them by score-adjusted market-cap as a factor strategy for momentum. The MSCI Minimum Volatility and MSCI Value-Weighted indices, which do not select stocks differently from the broad cap-weighted indices but reweight the stocks in the universe based on an optimisation (Minimum Volatility) or based on accounting measures (value-weighted) are proposed as factor indices for the low volatility and value factor respectively. For the size factor, MSCI favours capture of the size factor through an equal-weighted portfolio of the standard large and mid-cap stocks in the MSCI US index.

S&P publishe a Tilt index series which sorts stocks in the S&P1500 into deciles based on factor score and then over-weights the deciles with the higher factor scores for the low volatility, low valuation and momentum factors. For the size factor, S&P publishes indices based on market cap range such as the S&P Mid-cap index, which uses cap-weighting and provides exposure to the relatively smaller size segment.

It should be noted that, in addition to potential differences in performance due to distinct construction methodology, different index providers include implementation rules in their indices in order to avoid transaction costs for investors trying to capture the factor exposures. For example, the S&P and Russell indices have an implicit reference to market cap weights which naturally tends to ease implementation. The MSCI factor indices use different rules across different factors. For example, no investability adjustments are done for equal-weighted indices. The other

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factor indices use different adjustments such as a weight cap in the momentum index, turnover constraints in the min volatility index, and smoothing over average fundamental variables in the value-weighted indices. The ERI Scientific Beta indices apply investability rules (capacity and turnover control) as well as turnover constraints. While it is beyond the scope of this document to assess the implementation rules across providers, it is clear that factor indices potentially improve upon paper portfolios used to study factor premia in academic studies as far as investability is concerned.

Factor-based strategies are very popular not only among index providers but also among investment management firms. Many of those firms have created products that try to achieve high relative or absolute performance by having exposure to factors such as value, size and momentum. For example Dimensional Fund Advisors offer funds such as the USA Large Cap Equity Portfolio, which invests mainly in small, value and profitable stocks. AQR offers funds that either have single-factor exposures such as the Momentum Fund or the US Defensive Equity, which is a low volatility strategy, or combine factors such as momentum and size. Another firm that has created factor strategies is Robeco, with strategies such as the Momentum Equities and Value Equities. One potential drawback of all these strategies that investors should be aware of, is that these firms do not disclose any information regarding the investment methodology they follow. As a result they lack transparency and their performance totally depends on the skill of the fund manager.

• Multi-Factor Indices

When the strategy targets more than one risk factor, then it is categorised as a multi-factor index. Different providers offer multi-factor indices. The index providers use their single-factor indices and devise an allocation to these indices to come up with an index of indices as a multi-factor portfolio. The ERI Scientific Beta multi-factor indices combine the four main Scientific Beta multi-strategy factor indices in two ways – equal-weighting and equal risk contribution. Likewise, MSCI has combined its quality factor indices, value-weighted indices and Minimum Volatility indices into a multi-factor index referred to as quality mix. Other providers offer multi-factor indices without providing the sub-indices for individual factors. FTSE in partnership with JPMorgan produces a diversified multi-factor index which selects stocks based on criteria that relate to the value, low volatility, momentum and size factors. Goldman Sachs maintains an index which provides exposure to the value, momentum, quality, low volatility and size factors.

In fact, although these equity factor indices have different construction methodologies, a key question that any index provider faces is potential criticism that indices could be a result of a data mining exercise which in turn imply that factor indexing may not be robust over time.

Van Dijk (2011) reviews the subject of data mining and robustness. According to Black (1993), Lo and MacKinlay (1990), and MacKinlay (1995), most of the empirical studies that evidence the size effect or other asset pricing anomalies are based on the same data sample. Researchers then select and publish the

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most successful results, but without specifying the number of empirical computations they made before achieving these results. Thus, it is not possible to confer a statistical significance to the results and additional out-of-sample tests are needed to determine whether the anomalies identified are due to data mining or not.

In the same spirit, Harvey, Liu and Zhu (2014) argue that "hundreds of papers and factors attempt to explain the cross section of expected returns". The authors argue that, because of this extensive data mining, it is a serious mistake to use the usual statistical significance cut-offs (e.g. t-ratio exceeding 2.0) in asset pricing tests because many of the discovered factors would be considered "significant" by chance. The authors present several methodologies to test whether factors are significant or not, including a new one that particularly suits research in financial economics. They show that many of the factors discovered in finance are likely to be the result of data mining.

Kogan and Tian (2012) show that the performance of the factor models is highly related to the choice of the sample period, as well as to the methodology used to construct the factors, and thus may be quite unstable. Consequently, the authors suggest that "a data-snooping algorithm tends to pick spurious winners among the set of all possible models without revealing a robust underlying risk structure in returns".

In fact, although these equity factor indices have different construction methodologies, a key question that any index provider faces is potential criticism regarding robustness. A strategy is considered robust if it has the capacity to deliver risk-adjusted performance in the future to a degree that is comparable with that of the past owing to a well-understood economic mechanism rather than just by chance.

Lack of robustness in smart beta strategies is mainly caused by exposure to the following risks in the strategy construction process – factor fishing, model mining and non-robust weighting schemes.

<u>Factor Fishing Risks</u>

Harvey *et al.* (2014) document a total of 314 factors with a positive historical risk premium, showing that the discovery of the premium could be a result of data mining, i.e. strong and statistically significant factor premia may be a result of many researchers searching through the same dataset to find publishable results. For example, when capturing the value premium one may use extensive fundamental data including not only valuation ratios but also information on, for example, the sales growth of the firm. Therefore, a key requirement in investors accepting factors as relevant in their investment process is that there is a clear economic intuition as to why exposure to this factor constitutes a systematic risk (Kogan and Tian (2012)). Factors selected just based on past performance without considering any theoretical evidence are not robust and must not be expected to deliver a similar premium in the future.

Many index providers use composite and proprietary factors that are not well-established in the academic literature. As an illustration, MSCI uses four different variables for value and two proprietary definitions for momentum. Another example is the Goldman Sachs Equity

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Factor Index, which in order to have exposure to high quality stocks uses seven different variables. Finally, FTSE in order to construct the Developed Factor indices[45], conducted short-term back-testing and selected the best performing factor definitions.

Model Mining Risks

Model mining risk is the risk of having an index construction methodology which results in a good track record in back-testing. Many value-tilted indices include a large set of ad-hoc methodological choices, opening the door to data mining. As an illustration, one can consider the impact of various specification choices on fundamental equity indexation strategies, which are commonly employed as a way to harvest the value premium. Another example could be the non-linear algorithm employed as a weighting scheme used by Russell. Non-linear models in general are prone to over-fitting (see Lo 1994) and as a result the potential for model mining is high.

Non-robust weighting schemes

All smart beta strategies are exposed to unrewarded strategy-specific risks. Specific risks correspond to all the risks that are unrewarded in the long run, and therefore not ultimately desired by the investor. Many index providers, when constructing factor indices end up with highly concentrated strategies. This lack of diversification of unrewarded risks hampers the robustness of the strategy and it could underperform even in periods when the underlying factor performs well. For example indices that modify the cap weights by a factor score do not solve efficiently the problem of poor diversification and also do not guarantee maximum exposure.

Finally, another issue with factor indices in consistency. Investors should be sceptical when an index provider implements different weighting schemes, stock selection methodologies and risk controls among their indices. This is an approach that leaves the door of data mining open. For example, MSCI offers market-cap-adjusted indices for value and momentum, optimised for low volatility and equal weight for size.

Another approach to inconsistency is by looking at the evolution or change of methodology over time for the same strategy or the same factor. Russell launched new factor indices to create a new brand known as 'High Efficiency' (HE) indices when it already had the following factor indices on the market – Russell 1000 High Momentum, Russell 1000 Low Volatility and Russell 1000 Value. The new indices have the same objective as the old ones but different construction principles.

In general there are three ways by which the robustness of various smart beta strategies can be improved.

Avoidance of Data Mining through a Consistent Framework

A very effective mechanism to avoid data mining is by establishing a consistent framework for smart beta index creation, thus limiting the choices yet providing the flexibility needed for smart beta index creation. Consistency in the index framework has two main benefits. First, it prevents model mining by limiting the number of choices through which indices can be constructed. A uniform framework is the best safeguard against post hoc index design, or model mining (i.e. the possibility to test a large number of smart beta strategies, and publish the ones that have good results).

45 - See e.g. the paper "Factor Exposure Indices – Momentum Factor" <http://www.ftse.com/products/downloads/FTSE_Momentum_Factor_Paper.pdf>

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Second, analysis across specification choices is vital because the range of outcomes gives a more informative view than a single specification, which could always have been picked. An index that performs well across multiple specification choices is more robust than an index that performs only in a single specification choice, which could very well have been by chance rather than because of the robustness of the strategy. To be transparent about sensitivity to specification choices strategy providers could disclose the sensitivity of performance to such specification choices, thereby avoiding investors exposing themselves to a risk of unintended consequences of undesired risks.

Moreover, a consistent factor index design framework for the construction of smart beta strategies is a practical way of limiting the number of possibilities that analysts can search over and this should lead to more robust design.

3. Diversification Strategy Indices

3. Diversification Strategy Indices

Diversification strategies aim at delivering a fair risk-adjusted return over the long term by combining several risky assets in a portfolio in accordance with Modern Portfolio Theory (Markowitz, 1952). Such strategies invest across a variety of assets to benefit from the fact that their returns are not synchronous so that a loss on one asset may be compensated through the gain on another asset during the same time period. The portfolio construction methodologies underlying Diversification Strategy Indices aim at designing proxies for a portfolio that is optimal from a risk-return perspective (the tangency portfolio).

3.1 Heuristic vs Efficient Diversification Strategies: A Definition of the Construction Methodology and the Risk Specific to each Strategy

Modern Portfolio Theory prescribes that every rational investor should optimally seek to allocate wealth to risky assets so as to achieve the highest possible Sharpe ratio. Implementing this objective, however, is a complex task because of the presence of estimation risk for the required expected returns and covariance parameters. The costs of parameter estimation error may in some cases entirely offset the benefits of optimal portfolio diversification (see e.g. De Miguel *et al.*, 2009b). Therefore some methodologies for constructing Diversification Strategy Indices do not explicitly aim to obtain a portfolio with an optimal risk/reward ratio, but instead adopt heuristic approaches to diversification.

Among heuristic or ad-hoc strategies, one can further distinguish between *Deconcentration* and *Decorrelation*. *Deconcentration* strategies simply focus on balancing the portfolio's exposures by spreading out the constituents' weights or their risk contributions. This can be seen as a response to concerns about weight or risk concentration which may arise in cap-weighted equity indices. *Decorrelation* strategies go beyond that objective and focus explicitly on maximising the benefits that stem from the fact that assets are imperfectly correlated. As with deconcentration strategies, the objective of decorrelation strategies is not explicitly framed in terms of the risk-adjusted reward of the portfolio, and these can thus be seen as ad-hoc approaches to diversification.

In contrast to these heuristic approaches, scientific or *efficient diversification* methodologies are based on the theoretical framework of Modern Portfolio Theory and aim at obtaining risk/return efficient portfolios, i.e. portfolios that obtain the lowest level of volatility for a given level of expected return (and thus the highest risk-adjusted return). Thus efficient diversification goes beyond the objective of maximising variety in the portfolio either through maximising the number of exposures ("Deconcentration") or maximising how different the exposures are ("Decorrelation"), and rather focuses on maximising the risk-adjusted return resulting from these exposures. It should be noted that the heuristic and scientific approaches to diversification are not mutually exclusive – for instance, the motivation for the addition of weight constraints to a scientific diversification methodology can be to bring it closer to a heuristic methodology in order to gain robustness.

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We now will briefly describe three *heuristic diversification* strategies (Maximum Deconcentration, Diversified Risk Weighted and Maximum Decorrelation) and then two *efficient diversification* strategies, namely Efficient Minimum Volatility and Efficient Maximum Sharpe.

Equal-weighting is a simple way of "deconcentrating" a portfolio, thus allowing it to benefit from systematic rebalancing back to fixed weights. Depending on the universe and on whether additional implementation rules are used, the rebalancing feature of equal-weighting can be associated with relatively high turnover and liquidity problems. Maximum Deconcentration can be perceived as a generalisation of a simple equal-weighting scheme: the aim being to maximise the effective number of stocks. Maximum Deconcentration minimises the distance of weights from the equal weights subject to constraints on turnover and liquidity. In addition, investors have the option to add constraints on tracking error, sector weight deviations or country weight deviations with respect to the cap-weighted reference index. In the absence of any constraints, Maximum Deconcentration coincides with the equal-weighting (also known as the "1/N" weighting scheme), which owes its popularity mainly to its robustness and to the fact that it has been shown to deliver attractive performance despite highly unrealistic conditions of optimality, even in comparison to sophisticated portfolio optimisation strategies (De Miguel *et al.*, 2009b).

Extending the notion of deconcentration in terms of weights to deconcentration in terms of contributions to risk, the general Risk Parity approach aims to achieve diversification by equalising the contributions of constituent stocks to the total portfolio volatility. Formally, it seeks weights that satisfy the following condition, for all *i*, *j*:

$$w_i \frac{\partial \sigma_p}{\partial w_i} = w_j \frac{\partial \sigma_p}{\partial w_j} \tag{12}$$

where w_i is the (positive) portfolio weight of stock i and σ_p the portfolio volatility (see Maillard, Roncalli and Teïletche, 2010, for a detailed discussion). It should be noted that in the general case no analytical solution is available to this problem; it therefore needs to be solved numerically. Diversified Risk Weighted, which is based on a specific case of the general Risk Parity approach; it is a weighting scheme that attempts to equalise the individual stock contributions to the total risk of the index, assuming uniform correlations across stocks.

Going beyond the creation of balanced portfolios based on various forms of deconcentration, the Maximum Decorrelation strategy focuses explicitly on maximising the benefits of exploiting the correlation structure of stock returns. In fact, the Maximum Decorrelation approach attempts to achieve reduced portfolio volatility by estimating only the correlations across constituent stocks, while assuming their volatilities are identical, so as to avoid the risk of error in estimating expected returns and volatilities of individual stocks. The approach has in fact been introduced to measure the diversification potential within a given investment universe (Christoffersen *et al.*, 2010). Thus, just as the Maximum Deconcentration weighting scheme reduces concentration in a nominal sense, the Maximum Decorrelation weighting scheme reduces the correlation-adjusted concentration.

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In contrast with the three ad-hoc diversification strategies above, the true Minimum Volatility portfolio lies on the efficient frontier and coincides with the optimal portfolio of Modern Portfolio Theory (the tangency portfolio) if, and only if, expected returns are identical across all stocks. However, due to the presence of estimation risk affecting the input parameters, the Minimum Volatility portfolio is an attractive strategy because there is no need to estimate expected returns (only risk parameters need to be estimated). Thus, Minimum Volatility strategies can, in practice, hope to be decent proxies of truly efficient portfolios. To address the difficulties in risk parameter estimation, Minimum Volatility strategies typically employ different models for the robust estimation of risk parameters and/or different types of weight constraints (see e.g. Chan, Karceski and Lakonishok, 1999). Thus there is a wide variety of Minimum Volatility variants made available by index providers.

In line with Modern Portfolio Theory, the Efficient Maximum Sharpe Ratio strategy is an implementable proxy for the tangency portfolio. As in any mean-variance optimisation, the estimation of input parameters is a central ingredient in the implementation of the methodology. In contrast to Minimum Volatility strategies which only require estimates of risk parameters (volatilities and correlations), the Maximum Sharpe Ratio strategy relies on estimates of both risk parameters and expected returns. As direct estimation of expected returns is known to lead to large estimation errors (Merton, 1980), Amenc *et al.* (2011a) propose to use an indirect estimation of expected returns by assuming that they are positively related to a stock's downside risk which implies that the semi-deviations of stocks can be used as a proxy. Based on this parsimonious approach, it is possible to conduct an explicit Sharpe Ratio maximisation. While both the Efficient Minimum Volatility strategy and the Efficient Maximum Sharpe Ratio are proxies for portfolios on the efficient frontier, each of these methodologies are based on different explicit or implicit assumptions for optimality: the Maximum Sharpe Ratio approach explicitly assumes that there are differences in returns across stocks, while the Minimum Volatility approach implicitly assumes identical expected returns across stocks.

Finally, on top of these diversification-based weighting schemes, one can add an extra-layer of diversification, by "diversifying the diversifiers". Indeed, each particular weighting scheme presented above diversifies at the stock level, avoiding potentially fatal concentration in specific stocks. As demonstrated by Kan and Zhou (2007) and Amenc *et al.* (2012), combining the different weighting schemes helps in removing any remaining model risk. In this logic, Scientific Beta offers the Diversified Multi-Strategy approach, which combines the five different diversification-based weighting schemes in equal proportions so as to diversify away unrewarded risks and parameter estimation errors.[46] For detailed explanations of the mechanism at work behind the Diversified Multi-Strategy weighting scheme, we invite the reader to consult the dedicated Scientific Beta White Paper and the references therein.

We have presented here the rationale of the main approaches to diversification (i.e.

46 - To make a popular analogy, one can think of the Diversified Multi-Strategy approach as exploiting an effect similar to Surowiecki's (2004) wisdom-of-crowds effect by taking into account the "collective opinion" of a group of strategies rather than relying on a single strategy.

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heuristic versus efficient diversification strategies), then given a short description of the weighting schemes and shed light on their conditions of optimality and the risks specific to their construction methodologies. In the following section, we will turn to analysing the risk and performance properties of the diversification strategies discussed above.

3.2 Performances and Risks of Diversification-Based Weighting Schemes: An Empirical Illustration

In this section we compare the performance and risk characteristics of the available Scientific Beta Diversification Strategy Indices for the United States using Scientific Beta Long-Term Track Records. We will base our illustrations on the United States as this is probably the equity market that investors are most familiar with and as this ensures comparability with many other studies on smart beta investing. Furthermore, the use of 40 years of data allows for a robust evaluation of the different methodologies. The goal of this section is to highlight the key similarities and differences among the five Diversification Strategy Indices introduced above.

Risk and performance measures are reported both in absolute terms and in relation to the cap-weighted reference index. In fact, just as the volatility of returns is important as an absolute risk measure for investors who are interested in returns per se, the volatility of the return difference with the reference cap-weighted index (the so-called tracking error) becomes a relevant risk measure for investors who are concerned about risk relative to their reference index. One-way annual turnover is computed as the annualised sum of realised absolute deviation of individual stock weights across quarters. The weighted average market capitalisation of the index (expressed in $m) is a systematic metric that can be compared with that of the cap-weighted index to assess the liquidity of the strategy.

As shown in Table 18, all the diversification strategies Indices exhibit a similar level of returns of around 13.6% on the sample

Table 18: Absolute Performance and Implementation of Diversification Strategy Indices based on Scientific Beta Long-Term Track Records. This table shows the absolute performance and risk statistics over the analysis period of 40 years (from 31/12/1973 to 31/12/2013) for the five Scientific Beta USA indices. The results for the cap-weighted reference index of Scientific Beta USA are indicated in the leftmost column.

	Scientific Beta USA Long-Term Track Records						
Absolute Performance and Risk	Cap-Weighted	Maximum Deconcentration	Diversified Risk Weighted	Maximum Decorrelation	Efficient Minimum Volatility	Efficient Maximum Sharpe Ratio	Diversified Multi-Strategy
Annualised Returns	10.95%	13.60%	13.61%	13.64%	13.48%	13.84%	13.65%
Annualised Volatility	17.38%	17.41%	16.71%	16.62%	14.67%	15.93%	16.22%
Sharpe ratio	0.32	0.48	0.50	0.50	0.56	0.54	0.51
Sortino ratio	0.46	0.67	0.70	0.70	0.77	0.74	0.72
One-Way Turnover	2.67%	20.40%	22.13%	29.49%	30.18%	28.01%	20.34%
Capacity ($m)	47381	11464	12297	11447	13641	12254	12221

The statistics are based on daily total returns (with dividend reinvested). All statistics are annualised and performance ratios that involve the average returns are based on the geometric average, which reliably reflects multiple holding period returns for investors. The Sortino ratio indicates the average excess return adjusted for the amount of downside risk. This measure is an alternative to the Sharpe ratio, in that it replaces the standard deviation with a different risk measure. Turnover is mean annual one-way. ERI Scientific Beta uses the yield of the "Secondary Market US Treasury Bills (3M)" as the risk-free rate in US Dollars.

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period. The range of the indices' volatilities is greater: from 14.67% for the Scientific Beta USA Efficient Minimum Volatility index, which in this case achieves ex-post its objective of volatility reduction, to 17.41% for the Scientific Beta USA Maximum Deconcentration Index. In fact, the Efficient Minimum Volatility weighting displays the highest Sharpe ratio at 0.56. The Sharpe ratios of the other Diversification Strategy Indices are between 0.48 and 0.54. The fact that the Efficient Maximum Sharpe Ratio weighting achieves a Sharpe ratio that is second best in the panel provides yet more empirical evidence of the importance of being cognisant of parameter estimation risk when designing strategies: Efficient Minimum Volatility has the same objective as Efficient Maximum Sharpe Ratio but bears less estimation risk by assuming that every stock has the same level of expected returns. Last but not least, all diversification strategies have led to higher Sharpe and Sortino ratios than the cap-weighted reference index. Indeed, the Maximum Deconcentration strategy has a volatility that is similar to the volatility of the cap-weighted index, around 17.4%, but its returns are more than 2.65% higher. Diversified Risk Weighted and Maximum Decorrelation have a level of volatility lower than that of the cap-weighted reference index, and both exhibit higher returns. Finally, the two efficient diversification strategies, Efficient Minimum Volatility and Efficient Maximum Sharpe Ratio, not only outperform the cap-weighted reference index in terms of returns, but are able to do so while reducing substantially the volatility and the amount of downside risk. For example, the Efficient Minimum Volatility strategy exhibits a strong Sortino ratio of 0.77 compared to the Sortino ratio for the cap-weighted reference index, which is 0.46.

In addition, an implementation challenge of alternative weighting schemes is the higher levels of turnover they can incur. For instance, Plyakha, Uppal and Vilkov (2012), Demey, Maillard and Roncalli (2010) and Leote de Carvalho, Xu and Moulin (2012) have reported that equally-weighted strategies have moderately higher levels of turnover compared to market-capitalisation-weighted portfolios. Table 18 shows that the cap-weighted index has a mean one-way annual turnover of 2.67%, mainly[47] due to the deletion and addition of stocks to the Scientific Beta US universe. Maximum Deconcentration and Diversified Risk Weighted indices show a very reasonable level of turnover of around 20-22%. Similarly, the three other Diversification Strategy Indices have a higher turnover of about 28% to 30%. Overall, the turnover levels of the five Diversification Strategy Indices remain reasonable and thus these strategies can be implemented without incurring excessive transaction costs. It is noteworthy that Diversified Multi-Strategy presents the lowest turnover at 20.34%. Managing the five different weighting schemes internally allows for internal crossing of some trades, hence reducing the turnover compared to the turnover that would have been incurred by separate management of the five components. Finally, the weighted average market capitalisation of all strategies is around 1/4th that of the cap-weighted index, meaning that they are all adequately liquid. It should also be noted that this figure is an average over the last 40 years and is thus much lower than more recent values.

Even for investors who have chosen to make use of alternative weighting schemes, cap-weighted indices still remain the ultimate reference when it comes to evaluating the performance of alternative indices, because they are widely used as a market reference. Probability

47 - Potentially, corporate actions or changes in free-float could induce additional turnover in a cap-weighted index.

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of outperformance is the historical empirical probability of outperforming the benchmark over a typical investment horizon of 1 or 3 years, irrespective of the entry point in time. It is computed using a rolling window analysis with a 1- or 3-year window length and a 1-week step size. Table 19 displays summary statistics for the relative performance and relative risk of the five alternative indices (with respect to the cap-weighted reference index) over the analysis period of 40 years (from 31/12/1973 to 31/12/2013).

An examination of relative performances and risk in Table 19 provides a different picture of the Diversification Strategy Indices. All five strategy indices outperformed the Scientific Beta USA cap-weighted index by more than 2.5% during the period of study. Nonetheless they did so with different levels of tracking error: Efficient Maximum Sharpe Ratio provided the highest relative returns at 2.89% but also led to the second highest tracking error at 4.47%, resulting in an information ratio of 0.65. Even though in absolute risk-adjusted performance, Efficient Minimum Volatility was besting the other four weighting schemes, this result is contrasted by the lowest information ratio (0.48) due to a higher tracking error level (5.23%), An explanation for the relatively low tracking error levels observed for the Diversified Risk Weighted strategy lies in the fact that overweighting low volatility stocks leads to some extent to overweighting large cap stocks (see e.g. Chan, Karceski and Lakonishok, 1999). The relative risks of the Diversified Risk Weighted strategy compared to the cap-weighted reference index are therefore very well rewarded. Also, the fact that Minimum Volatility strategies lead to substantial levels of tracking error is well-documented in the literature and has been attributed to the fact that they exhibit low market beta compared to their cap-weighted reference (see e.g. Chan, Karceski and Lakonishok, 1999, or Baker *et al.*, 2011, for related evidence on tracking error of low volatility portfolios). As we show in the white paper dedicated to Efficient Minimum Volatility Strategies, one can also relate this to the more pronounced sector deviations of the strategy that admittedly

Table 19: Relative Performance of Diversification Strategy Indices with regard to the cap-weighted reference index, based on Scientific Beta Long-Term Track Records. This table shows the relative performance and risk statistics with regard to the cap-weighted reference index for the five Scientific Beta USA indices over the analysis period of 40 years (from 31/12/1973 to 31/12/2013).

	Scientific Beta USA Long-Term Track Records					
Relative Performance and Risk	Maximum Deconcentration	Diversified Risk Weighted	Maximum Decorrelation	Efficient Minimum Volatility	Efficient Maximum Sharpe Ratio	Diversified Multi-Strategy
Annualised Excess Returns	2.65%	2.66%	2.69%	2.53%	2.89%	2.70%
Tracking Error	4.25%	4.16%	4.29%	5.23%	4.47%	4.21%
Information Ratio	0.62	0.64	0.63	0.48	0.65	0.64
Outperformance Probability (1 year)	65.37%	69.25%	71.27%	71.86%	71.17%	72.25%
Outperformance Probability (3 year)	72.67%	76.19%	78.93%	79.66%	80.02%	78.47%

The statistics are based on daily total returns (with dividend reinvested). All statistics are annualised and performance ratios that involve the average returns are based on the geometric average, which reliably reflects multiple holding period returns for investors. The cap-weighted reference index used is theScientific Beta USA cap-weighted index. ERI Scientific Beta uses the yield of the "Secondary Market US Treasury Bills (3M)" as the risk-free rate in US Dollars. Information Ratio is computed as the excess return of a strategy over the cap-weighted reference index adjusted for its tracking error.

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concentrate on low volatility stocks. It is interesting to see that all strategies have a high probability of outperformance for a 3-year investment horizon. Maximum Deconcentration has a 73% outperformance probability with a relative return of 2.65% and Efficient Minimum Volatility has an 80% outperformance probability with a relative return of 2.53%. Finally, one should note also that Diversified Multi-Strategy presents the average outperformance of the five diversification-based strategies, and a lower-than-average tracking error, resulting in an information ratio of 0.64. In addition, the probability of outperformance of the Diversified Multi-Strategy is better than the average, especially at short horizons.

Strategies that exhibit attractive returns adjusted by their "normal risk" (as measured by volatility) can still experience periods of extreme losses. We now seek to identify the occurrence of those extreme losses for each strategy. To that end, we study extreme risk measures such as the Historical VaR, which corresponds to the 5th percentile of the distribution of returns, and a Cornish-Fisher VaR which takes into account the skewness and kurtosis of returns, which are admittedly not normally distributed. Table 20 shows summary statistics for the Diversification Strategies' extreme risk from 31/12/1973 to 31/12/2013. In addition to the VaR measures, the table reports the maximum historical drawdown.

As displayed in Table 20, the Diversified Risk Weighted and Maximum Decorrelation strategies exhibit similar extreme risk statistics, with comparable Historical VaR (about 1.50%) or Cornish-Fisher 5% VaR (around 1.45%). However the maximum drawdown figure of Diversified Risk Weighted is about 2% higher than for the Maximum Decorrelation strategy. The Efficient Maximum Sharpe Ratio weighting is marginally less exposed to extreme risk than the latter two strategies (the VaR measure for this strategy index is 0.07% lower than for the same measure for the Diversified Risk Weighted and Maximum Decorrelation strategy indices and the maximum drawdown is about 1% lower). Maximum Deconcentration displays the highest extreme risk levels, which is not surprising since its construction and optimisation do not take any risk parameters into account. Extreme risk measures reveal that in comparison to the cap-weighted reference index, the diversification strategies display either similar VaR and maximum drawdown levels (in the case of Diversified Risk Weighted, Maximum Decorrelation) or slightly lower VaR levels

Table 20: Extreme Risk of Diversification Strategy Indices based on Scientific Beta Long-Term Track Records. This table shows the extreme risk statistics for the five Scientific Beta USA indices over the analysis period of 40 years (from 31/12/1973 to 31/12/2013). The results for the cap-weighted reference of Scientific Beta USA Long-Term Track Records are indicated in leftmost column.

	Scientific Beta USA Long-Term Track Records						
Extreme Risk	Cap-Weighted	Maximum Deconcentration	Diversified Risk Weighted	Maximum Decorrelation	Efficient Minimum Volatility	Efficient Maximum Sharpe Ratio	Diversified Multi-Strategy
Cornish-Fisher 5% VaR	1.51%	1.53%	1.45%	1.46%	1.21%	1.38%	1.40%
Historical 5% VaR	1.58%	1.55%	1.49%	1.50%	1.31%	1.43%	1.45%
Maximum Drawdown	54.53%	58.70%	56.36%	54.16%	50.03%	53.22%	54.55%

The statistics are based on daily total returns (with dividend reinvested). The Historical 5% Value-at-Risk measure indicates the 5th percentile of the historical return distribution. The Cornish-Fisher extension adjusts the VaR in the presence of skewness and / or excess kurtosis different from zero. It should be noted that VaR figures are daily loss figures, therefore a positive value indicates a loss. Maximum Drawdown represents the largest single drop from peak to bottom in the index value.

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and maximum drawdowns (in the case of Efficient Maximum Sharpe Ratio and Diversified Multi-Strategy). The Maximum Deconcentration strategy exhibits over the 40-year sample the highest Cornish-Fisher and Historical Value-at-Risk and a more significant maximum drawdown than the other weighting schemes. In contrast, Efficient Minimum Volatility, which solely focuses on risk reduction, shows extreme risk levels significantly below the other indices and the cap-weighted reference index, be it in terms of Cornish-Fisher and Historical Value-at-Risk, or in terms of maximum drawdown. Indeed, Efficient Minimum Volatility has a VaR level lower than Maximum Deconcentration and a maximum drawdown that is lower by 8.67%. Overall, these findings on extreme risks are quite consistent with what we have observed in Table 18 when using volatility as a risk measure.

Rather than relying on an assessment of the past performance of a strategy, it is important to gain a clear understanding of the associated style biases involved. Indeed, investors should be aware of all the factors that explain the performance of their portfolio. Any alternative weighting scheme can (sometimes implicitly) lead to exposures to certain well-known systematic risk factors or to important sector deviations from the cap-weighted reference index.

3.3 Risk Factor Exposures of Diversification Strategy Indices

As the consensus in academic finance and among practitioners suggests, the single market factor used in the CAPM model does not fully explain the cross section of expected stock returns. This has led to the development of multi-factor models that account for a range of priced risk factors. Here, we employ the Carhart four-factor model to assess exposures of the five diversification strategies to well-known systematic factors: the market factor as represented by the market cap-weighted reference index; the small-cap factor (Small-Minus-Big or SMB); the value factor (High-Minus-Low or HML), and the momentum factor (Winners-Minus-Losers or WML) (see Fama and French, 1992 and Carhart, 1997). Table 21 shows the coefficient estimates and R^2 of the regression of the indices' excess returns (over the risk-free rate) on the four Carhart factors over the last 40 years.

Table 21 shows that the Maximum Deconcentration strategy index has the most neutral market beta at 0.99, relative to the cap-weighted reference index (whose market beta is one by definition). The fact that this strategy is the least defensive is consistent with the fact that all the other diversification strategies rely on risk parameters to achieve diversification. Indeed, the Efficient Minimum Volatility weighting demonstrates the most defensive character with a market beta at 0.82. This must be related to the fact that, in this strategy, risk reduction is achieved along both the lines of correlation and volatility.[48] An interesting fact is the rather defensive aspect of the Efficient Maximum Sharpe Ratio strategy index, whose market beta of 0.91 can be linked to the construction assumptions of this weighting scheme. Indeed, in this strategy the semi-deviations of the constituent stocks are used as an input to proxy for their expected returns in order to avoid direct estimation of returns (which is known to suffer from large estimation errors[49]). Following this, one could expect the strategy to be biased towards high semi-deviation stocks and thus lead to a higher market beta for the portfolio. Nevertheless, the objective of the strategy is not to maximise returns, but

48 - This is in line with many empirical studies in the literature reporting low market betas for minimum volatility strategies (see for instance Chan, Karceski and Lakonishok, 1999, or Scherer, 2011). Additionally, it should be noted that since the Efficient Minimum Volatility uses norm constraints to avoid over concentration in low volatility stocks, the observed market betas of this strategy tend to be markedly lower than one but not as low as in other studies where such constraints are not imposed.

49 - For a complete description of the Scientific Beta Efficient Maximum Sharpe ratio strategy, we refer the reader to the Strategy White Paper on Efficient Maximum Sharpe Ratio Indices.

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Table 21: Systematic Risk factor exposures of Diversification Strategy Indices based on Scientific Beta Long-Term Track Records. This table shows the coefficient estimates and R-squared of the regression of excess returns of the five Scientific Beta USA indices over the risk-free rate using the Carhart four-factor model over the analysis period of 40 years (from 31/12/1973 to 31/12/2013).

	Scientific Beta USA Long-Term Track Records					
Coefficient	Maximum Deconcentration	Diversified Risk Weighted	Maximum Decorrelation	Efficient Minimum Volatility	Efficient Maximum Sharpe Ratio	Diversified Multi-Strategy
Alpha (Annualised)	1.27%	1.58%	1.37%	2.09%	1.76%	1.62%
Market Beta	0.99	0.95	0.95	0.82	0.91	0.93
Size Beta	0.21	0.16	0.20	0.10	0.16	0.17
Value Beta	0.11	0.11	0.09	0.10	0.11	0.11
Momentum Beta	-0.05	-0.04	0.01	0.01	0.02	-0.01
R^2	97.36%	96.76%	96.58%	93.73%	95.85%	96.63%

The data are daily total returns (with dividend reinvested). The Market factor is the daily return of cap-weighted index of all stocks in excess of the risk-free rate. Small size factor is long the CW portfolio of market cap deciles 6 to 8 (NYSE, NASDAQ, AMEX) and short the CW portfolio of the largest 30% of stocks. Value factor is long the CW portfolio of the highest 30% and short the CW portfolio of the lowest 30% of B/M ratio stocks. Momentum factor is long the CW portfolio of the highest 30% and short the CW portfolio of the lowest 30% of 52-week (minus most recent 4 weeks) past return stocks. The regression coefficients (betas and alphas) statistically significant at the 5% level are highlighted in bold. Complete stock universe consists of 500 largest stocks in USA. The yield on secondary market US Treasury Bills (3M) is the risk-free rate.

rather to maximise the Sharpe ratio. The estimated vector of expected stock returns is therefore adjusted by the corresponding covariance estimates. It turns out that the optimisation slightly favours low risk (and low beta) stocks, resulting in a greater emphasis on volatility reduction than on increasing the relative weights of high semi-deviation stocks to profit from the potentially higher returns they would bring to the portfolio. Yet, this defensive bias is far less pronounced than in the case of the Efficient Minimum Volatility strategy, whose sole objective is to reduce the total portfolio volatility.

Any strategy that deconcentrates weights compared to a cap-weighted index which, by construction, allocates higher weights to the largest stocks will mechanically introduce a size tilt towards smaller capitalisation stocks. As shown in Table 21, for this reason all of the five Diversification Strategy Indices exhibit a small-cap tilt. It is worth noting that the Maximum Deconcentration strategy has the largest exposure to the size factor (0.20), more than twice that of the Efficient Minimum Volatility strategy (0.10). In fact, equal-weighting, by construction, will grant more weight to the smallest stocks (by market capitalisation) than other schemes. On the other hand, Minimum Volatility strategies are known to tend to concentrate in low volatility stocks, and low volatility stocks correspond to some extent to large capitalisation stocks.[50] The fact that the Maximum Decorrelation strategy index displays the second highest exposure to the small-cap factor can be attributed to its sole focus on correlations. Indeed, Petrella (2005) shows that including small-cap stocks in an all-size portfolio decreases its total average correlation as smaller capitalisation stocks tend to have a lower correlation with larger capitalisation stocks than larger cap stocks do among themselves. Additionally, Eun, Huang and Lei (2008) show that smaller-cap stocks are less correlated with each other than large cap stocks because the underlying return-generating mechanisms for small-cap stocks are more company specific than those for large cap stocks.

Based on these findings about small-cap stocks, one would indeed expect the Maximum Decorrelation strategy index,

50 - This effect is also reported by Chan, Karceski and Lakonishok (1999).

3. Diversification Strategy Indices

which over-weights stocks that have low correlation with other stocks in the universe, to be more heavily exposed to the smaller-cap stocks of the universe. In addition, the five weighting schemes lead to positive exposures to the value factor, with a HML beta of 0.11.

So far we have analysed the exposure of the Diversification Strategy Indices to systematic risk factors. However, it is possible to control the exposures to these risk factors according to the needs of an investor. In the following section, we will analyse the effects of modifying the stock universe to which the weighting scheme is applied, on various performance and risk objectives. We will use Diversified Multi-Strategy factor indices representing a set of four well-documented and popular risk factors – value, momentum, low volatility and size.

3.4 Neutralising or Accentuating Factor Tilts of Diversification-Based Strategies Through Stock Selection: An Empirical Illustration

Weighting schemes are in general not immune to embedded systematic factor exposures such as value and small-cap tilts, or tilts towards less liquid stocks (cf. Table 21). A key difference of the weighting phase compared to the stock selection phase is that the factor tilts resulting from the weighting scheme are often much more implicit. The selection step proves to be a useful tool in explicitly controlling for unwanted systematic factor tilts that may arise from the choice of the weighting scheme. A clear distinction between the stock selection phase and the weighting phase allows for the modification of implicit factor tilts that may arise from the weighting scheme through an explicit choice of where the strategy invests (stock selection). More importantly, selection schemes can be used in conjunction with weighting schemes towards the achievement of a common objective. The control of systematic risk using stock selection has significant advantages as it is explicit and simple to understand. We stress that to accept factors as relevant in their investment process, investors should require a clear economic intuition as to why the exposure to this factor constitutes a systematic risk that

Table 22: Factor exposures of Multi-Strategy Factor Indices, based on Scientific Beta Long-Term Track Records. This table shows the coefficient estimates and R-squares of the regression of the excess returns of Multi-Strategy Factor Indices over the risk-free rate for four factor tilts – mid-cap, high momentum, low volatility, and value - using the Carhart four-factor model, over the analysis period of 40 years (from 31/12/1973 to 31/12/2013).

	Scientific Beta USA Diversified Multi-Strategy Long-Term Track Records				
Coefficient	Broad (No Selection)	Low Vol.	Mid-Cap	Value	Momentum
Alpha (Annualised)	1.62%	2.85%	2.66%	2.33%	1.84%
Market Beta	0.93	0.78	0.93	0.91	0.94
Size Beta	0.17	0.02	0.31	0.16	0.16
Value Beta	0.11	0.14	0.16	0.31	0.09
Momentum Beta	-0.01	0.00	0.00	0.03	0.17
R^2	96.63%	90.14%	92.20%	95.00%	95.52%

The data are daily total returns (with dividend reinvested). The Market factor is the daily return of cap-weighted index of all stocks in excess of the risk-free rate. Small size factor is long the CW portfolio of market cap deciles 6 to 8 (NYSE, NASDAQ, AMEX) and short the CW portfolio of the largest 30% of stocks. Value factor is long the CW portfolio of the highest 30% and short the CW portfolio of the lowest 30% of B/M ratio stocks. Momentum factor is long the CW portfolio of the highest 30% and short the CW portfolio of the lowest 30% of 52-week (minus most recent 4 weeks) past return stocks. The regression coefficients (betas and alphas) statistically significant at the 5% level are highlighted in bold. Complete stock universe consists of 500 largest stocks in USA. The yield on secondary market US Treasury Bills (3M) is the risk-free rate.

3. Diversification Strategy Indices

requires a reward and is likely to continue producing a positive risk premium. We show in the table above the factor exposures of the Diversified Multi-Strategy with and without stock selection.

We see in the table that for a given choice of factor, the stock selection veritably helps in shifting the corresponding factor exposure in the right direction. For instance, the table indicates that selecting low volatility stocks reduces the market exposure from 0.93 to 0.78. Similarly, the selection of mid-cap stocks leads to an increase in the SMB beta from 0.17 to 0.31.

Diversification-based strategies will incur transaction costs as they update weights as information on risk and expected return parameters is updated in the portfolio construction process. We discuss in the following section how transaction costs are managed and turnover is controlled for diversification-based strategies.

3.5 Managing Implementation Risks: Turnover and Trading Costs

One of the implementation challenges of alternative weighting schemes is the higher levels of turnover they can incur. For instance, Plyakha, Uppal and Vilkov (2012), Demey, Maillard and Roncalli (2010) and Leote de Carvalho, Xu and Moulin (2012) have reported that equally-weighted strategies have moderately higher levels of turnover compared to market capitalisation weighted portfolios.

In fact, the Scientific Beta indices discussed above are based on a universe of stocks belonging to the larger capitalisation range and that have been subjected to liquidity screens. Thus, the Scientific Beta universe for the US contains 500 stocks. In such a universe, liquidity issues are limited and diversification strategies can be implemented with ease. In order to further foster liquidity in the resulting index, additional adjustments of weights are implemented to achieve two objectives: one is to limit liquidity issues that may arise upon investing and another is to limit the liquidity issues that may occur upon rebalancing a strategy. The principle used to make such adjustments is to impose a threshold for the weight of a stock and for the weight change at rebalancing, relative to the market-cap-weight of the stock in its universe.[51]

Moreover, Scientific Beta indices are also governed by an optimal turnover control technique which is based on rebalancing thresholds (Leland, 1999; Martellini and Priaulet, 2002). At each quarterly rebalancing date, we look at the newly optimised weights of the strategy portfolio. These weights will not be implemented if the resulting overall weight change remains below the threshold. The threshold is calibrated using the past data, and it is fixed at the level that would have resulted in no more than a 30% annual one-way turnover historically. The idea behind this rule is to avoid rebalancing when deviations of new optimal weights from the current weights are relatively small. This technique brings down transaction costs by a large extent without having a substantial impact on the strategy's performance.

51 - Specifically, liquidity adjustments consist of two rules:
Rule 1 - We cap the stock's weight to a maximum of 10 times the free-float adjusted market cap-weight.
Rule 2 - In order to limit the impact of the rebalancing of weights on liquidity, we cap the change in weight for each stock to its free-float adjusted market cap-weight. This means that we avoid large rebalances of the smallest stocks.
Note that after re-normalising weights, the effective multiple will change again so that effectively the index could weight some stocks at a higher multiple of their cap-weight. In case of the occurrence of an effective optimal rebalancing, the fact that we apply liquidity adjustments will also shift the resulting weights from the in-sample optimal weights, in favour of ensuring out-of-sample ease of implementation.

4. Portfolio Construction Across Alternative Equity Beta Strategies

4. Portfolio Construction Across Alternative Equity Beta Strategies

An important question is how to allocate across a number of different risk factors to come up with an overall allocation that suits the investor's objectives and constraints. While it is beyond the scope of this section to provide an exhaustive framework for factor allocation, we illustrate the use of factor indices in two different allocation contexts, one aiming at improving absolute risk-adjusted returns, and one targeting relative risk objectives.

In what follows, we provide practical illustrations of multi-factor allocations drawing on smart factor indices, representing a set of four well-documented and popular risk factors, value, momentum, low volatility and size. To be more specific, we will use the Diversified Multi-Strategy approach, which combines five different diversification-based weighting schemes in equal proportions so as to diversify away unrewarded risks and parameter estimation errors (Kan and Zhou (2007), Amenc *et al.* (2012)[52]).

52 - To make a popular analogy, one can think of the Diversified Multi-Strategy approach as exploiting an effect similar to Surowiecki (2004)'s wisdom-of-crowds effect by taking into account the "collective opinion" of a group of strategies rather than relying on a single strategy.

4.1 The Rationale for Multi-factor Allocation: Why Combine Factor Indices?

Using smart beta indices as well-diversified ingredients that provide exposure to desired risk factors, we now analyse the potential benefits of combining factor tilts ("multi-beta allocations").

There is strong intuition suggesting that multi-factor allocations will tend to result in improved risk-adjusted performance. In fact, even if the factors to which the factor indices are exposed are all positively rewarded over the long-term, there is extensive evidence that they may each encounter prolonged periods of underperformance. More generally, the reward for exposure to these factors has been shown to vary over time (see e.g. Harvey (1989); Asness (1992); Cohen, Polk and Vuolteenaho (2003)). If this time variation in returns is not completely in sync for different factors, allocating across factors allows investors to diversify the sources of their outperformance and smooth their performance across market conditions. In short, the cyclicality of returns differs from one factor to the other, i.e. the different factors work at different times.

Intuitively, we would expect pronounced allocation benefits across factors which have low correlation with each other. As shown in Table 23, the correlation of the relative returns of the four smart factor indices over the cap-weighted benchmark is far below one. This entails in particular that a combination of these indices would lower the overall tracking error of the portfolio significantly. On a side note, the same analysis done conditionally for either bull or bear market regimes leads to similar results.

More generally, in an asset allocation context Ilmanen and Kizer (2012) showed that factor diversification was more effective than the traditional asset class diversification method, and that the benefits of factor diversification are still very meaningful for long-only investors.

Moreover, investors may benefit from allocating across factors in terms of implementation. Some of the trades necessary to pursue exposure to different factors may actually cancel each other out. Consider the example of an investor who pursues an allocation across a value and a momentum tilt. If some of the low valuation stocks with high weights in the value strategy start to rally, their

4. Portfolio Construction Across Alternative Equity Beta Strategies

Table 23. – Correlation of Relative Returns across Factor-Tilted Multi-Strategy Indices – The table shows the correlation of the relative returns of four Scientific Beta Factor-Tilted Multi-Strategy Indices (mid-cap, momentum, low volatility, and value) over the cap-weighted benchmark., The analysis is based on daily total return data from 31 December 1972 to 31 December 2012 (40 years) in panel A and from 31 December 2003 to 31 December 2013 (10 years) in panel B. The S&P 500 index and SciBeta Global Developed CW index are used respectively as the cap-weighted reference for US Long-Term Track Records and SciBeta Global Developed Investable Indices.

Panel A –Relative Returns Correlation Matrix - US Long-Term Track Records

US Long-Term Track Records (1973-2012)		Diversified Multi-Strategy			
		Low Volatility	Mid-Cap	Value	Momentum
Diversified Multi-Strategy	Low Volatility	100%	65%	71%	64%
	Mid-Cap		100%	86%	69%
	Value			100%	66%
	Momentum				100%

Panel B –Relative Returns Correlation Matrix - SciBeta Global Developed Indices

SciBeta Investable Global Developed Indices (Dec 2003 – Dec 2013)		Diversified Multi-Strategy			
		Low Volatility	Mid-Cap	Value	Momentum
Diversified Multi-Strategy	Low Volatility	100%	53%	26%	45%
	Mid-Cap		100%	49%	66%
	Value			100%	17%
	Momentum				100%

weight in the momentum-tilted portfolio will tend to increase at the same time as their weight in the value-tilted portfolio will tend to decrease. The effects will not cancel out completely, but some reduction in turnover can be expected through such natural crossing effects.

We now turn to a detailed analysis of the two key benefits of multi-factor allocations, namely the performance benefits and the implementation benefits.

4.2. Performance Benefits of Allocating Across Factors

Investors may use allocation across factor tilts to target an absolute (Sharpe ratio, volatility) or relative (information ratio, tracking error with respect to broad cap-weighted index) risk objective. We show in Table 24 the performance and risk characteristics of two multi-beta allocations in the US stock market over a 40-year track record and in the Developed excluding US universe over the last 10 years. The first one is an equal-weight allocation of the four smart factor indices (low volatility, mid-cap, value, and momentum). This allocation is an example of a simple and robust allocation to smart factors, which is efficient in terms of absolute risk. The second one combines the four smart factor indices so as to obtain equal contributions (see Maillard *et al.* (2010)) to the tracking error risk from each component index. This approach is an example allocation with a relative risk objective consistent with risk-parity investing[53]. Both multi-beta allocations are rebalanced quarterly. Of course, the multi-beta multi-strategy equal weight (EW) and equal risk contribution (ERC) indices are starting points in smart factor allocation. More sophisticated allocation approaches (e.g. conditional strategies, or strategies that are not agnostic on the rewards of the different smart factor

53 - Maillard *et al.* (2010) discuss a weighting scheme which equalises each asset's contribution to absolute risk, i.e. portfolio volatility. It is straightforward to extend their approach by applying it to relative returns with respect to a cap-weighted reference index. In this case, the objective is to equalise the contribution of each constituent to the overall relative risk (tracking error) with respect to the chosen reference index.

4. Portfolio Construction Across Alternative Equity Beta Strategies

indices) can be deployed using smart factor indices as ingredients to reach more specific investment objectives (see Amenc, Goltz and Thabault (2014b)).

Table 24 shows that both the multi-beta multi-strategy EW and ERC indices present returns that are close to the average returns of the constituents but lower absolute and relative risk than the average constituent index. Both allocations thus deliver improvements in risk-adjusted returns compared to the average constituent index. One should note that the EW allocation delivers the highest Sharpe ratio (0.52 in the US, 0.56 in the Developed universe) which, compared to the broad cap-weighted reference (0.24 in the US, and 0.36 in Developed universe), represents a relative Sharpe ratio gain of 115% in the US data and more than 50% in the Developed universe. One can also note that the allocation across several smart factor indices allows the tracking error to be reduced with respect to the cap-weighted reference index. Indeed, one witnesses impressive improvements for the multi-factor allocations compared to the average of their component indices in terms of relative risk, where both in the US and in the Developed universe, the reduction in the tracking error is around 0.70% for the EW allocation and 1% for the ERC allocation (which represent a risk reduction of about 11.5% for the EW allocation and more than 16% for the ERC allocation relative to the average tracking error of the component indices in the US case). This tracking error reduction yields an increase in the information ratios to levels of 0.76 and 0.77 from an average information ratio for the constituent indices of 0.67 in the US, while in the Developed region the average constituent information ratio is 0.78 and the multi-beta indices deliver even higher information ratios at 0.98 and 1.05 respectively for the EW and ERC allocations. Such improvements in the information ratio, of 26% and 35% for the EW and ERC allocations respectively in the Developed universe, are considerable and support the idea of diversification between smart factors. Moreover, compared to the average of their constituent indices, the multi-beta multi-strategy indices also exhibit significantly lower extreme relative risk (95% Tracking Error and maximum relative drawdown). In the Developed universe, the maximum relative drawdowns of the multi-beta indices are actually lower than those of any of the constituent indices. It is noteworthy that – due to its focus on balancing relative risk contributions of constituents – the ERC allocation provides greater reductions in the relative risk measures such as the tracking error and the extreme tracking error risk.

Briefly stated, the multi-beta allocations provide the average level of returns of their component indices. However, factor diversification leads to a risk reduction that is particularly strong in relative terms, which eventually results in risk-adjusted performance which is well above average. Additionally, the benefits of allocation across different factors can be seen in the probability of outperformance, which is the historical frequency with which the index will outperform its cap-weighted reference index for a given investment horizon. The results in Table 24 suggest that the probability of outperformance increases substantially for the multi-beta indices compared to the average across component indices, especially at short horizons. The higher probabilities of outperformance reflect the smoother and more robust outperformance resulting from the combination of different

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Table 24 – Performances and Risks of Multi-Beta Multi-Strategy Allocations vs Single-Factor Tilts – The table compares performances and risks of Scientific Beta Diversified Multi-Strategy indices on US Long-Term Track Records (Panel A) and SciBeta Developed Indices. The Multi-Beta Multi-Strategy EW Allocation is the equal combination of the four Factor-Tilted Diversified Multi-Strategies (low volatility, mid-cap, value, and momentum). The Multi-Beta Multi-Strategy ERC Allocation is an optimised combination of the four tilted indices in which beginning of quarter optimal allocations to the component indices are determined from the covariance of the daily relative returns of the component indices over the last 6 quarters (18 months), so as to obtain (in-sample) equal contributions to the (tracking error) risk. The analysis is based on daily total return data from 31 December 1972 to 31 December 2012 (40 years) in panel A and from 31 December 2003 to 31 December 2013 (10 years) in panel B. The S&P 500 index and SciBeta Developed CW index are used respectively as the cap-weighted reference for US Long-Term Track Records and SciBeta Developed Indices. Yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate.

Panel A

US Long-Term Track Records (Dec 1972 – Dec 2012)	USA Long-Term Cap-Weighted	Scientific Beta Diversified Multi-Strategy						
		Smart Factor Indices				Average of 4 Smart Factor Indices	Multi-Beta Allocations	
		Low Vol.	Mid-Cap	Value	Momentum		EW	ERC
Annual Returns	9.74%	12.64%	14.19%	14.44%	13.30%	13.64%	13.72%	13.53%
Annual Volatility	17.47%	14.39%	16.73%	16.55%	16.30%	15.99%	15.75%	15.69%
Sharpe Ratio	0.24	0.50	0.52	0.54	0.48	0.51	0.52	0.51
Max DrawDown	54.53%	50.13%	58.11%	58.41%	49.00%	53.91%	53.86%	53.30%
Excess Returns	-	2.90%	4.45%	4.70%	3.56%	3.90%	3.98%	3.79%
Tracking Error	-	6.17%	6.80%	5.82%	4.88%	5.92%	5.23%	4.91%
95% Tracking Error	-	11.53%	11.56%	10.14%	8.58%	10.45%	8.95%	8.11%
Information Ratio	-	0.47	0.66	0.81	0.73	0.67	0.76	0.77
Outperf. Prob. (1Y)	-	67.83%	67.88%	70.87%	68.42%	68.75%	73.87%	74.17%
Outperf. Prob. (3Y)	-	76.35%	74.12%	78.83%	84.42%	78.43%	80.38%	80.90%
Max Rel. DrawDown	-	43.46%	42.06%	32.68%	17.28%	33.87%	33.65%	28.74%

Panel B

SciBeta Investable Developed Indices (Dec 2003 – Dec 2013)	Developed Cap-Weighted	Scientific Beta Diversified Multi-Strategy						
		Smart Factor Indices				Average of 4 Smart Factor Indices	Multi-Beta Allocations	
		Low Vol.	Mid-Cap	Value	Momentum		EW	ERC
Annual Returns	7.80%	10.54%	10.45%	10.21%	10.30%	10.37%	10.41%	10.35%
Annual Volatility	17.09%	13.79%	16.12%	17.23%	16.09%	15.81%	15.68%	15.96%
Sharpe Ratio	0.36	0.65	0.55	0.50	0.54	0.56	0.56	0.55
Max DrawDown	57.13%	49.55%	54.57%	57.32%	54.35%	53.95%	53.94%	53.99%
Excess Returns		2.73%	2.65%	2.40%	2.49%	2.57%	2.61%	2.55%
Tracking Error		4.40%	3.33%	2.34%	3.70%	3.44%	2.65%	2.42%
95% Tracking Error		8.33%	6.23%	3.69%	7.24%	6.37%	5.07%	4.68%
Information Ratio		0.62	0.79	1.03	0.67	0.78	0.98	1.05
Outperf. Prob. (1Y)		67.66%	78.51%	74.89%	75.96%	74.26%	77.45%	80.64%
Outperf. Prob. (3Y)		93.17%	88.80%	83.06%	79.23%	86.07%	97.54%	100.00%
Max Rel. DrawDown		9.20%	6.77%	5.79%	12.00%	8.44%	6.37%	5.54%

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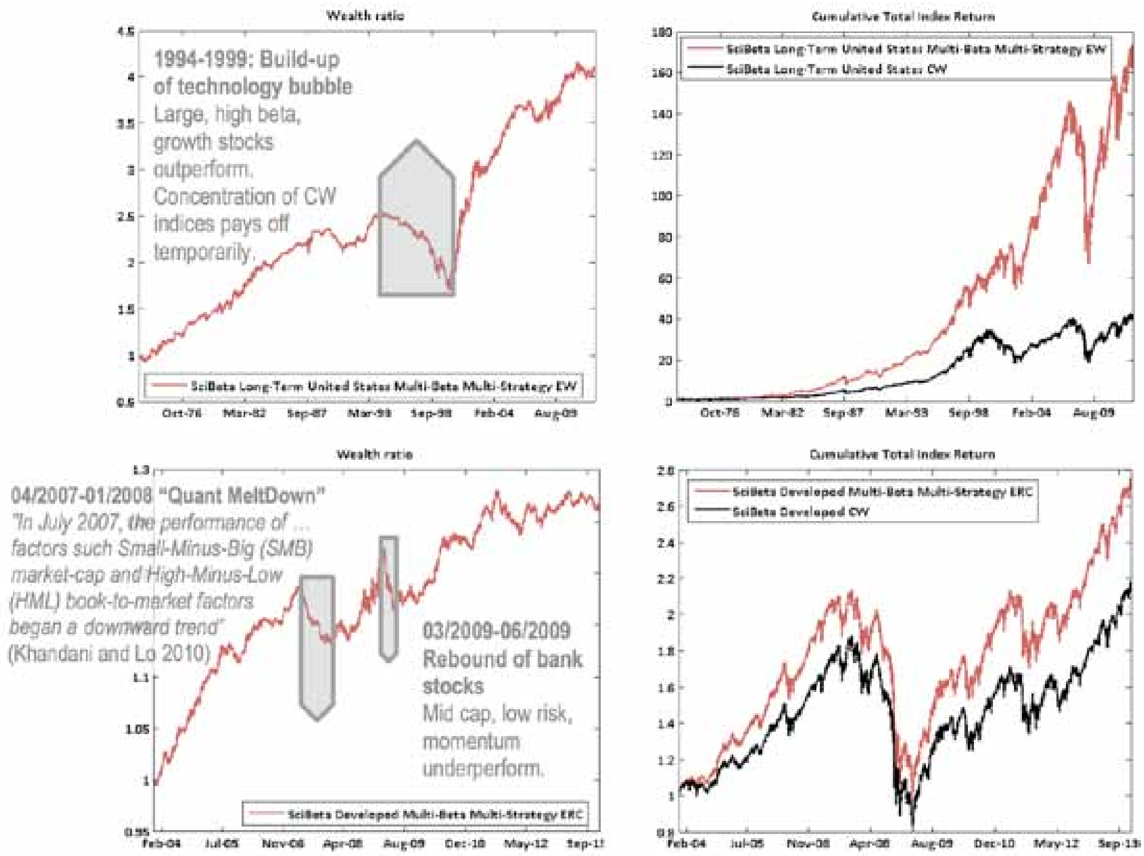
rewarded factors within a multi-beta index. The outperformance of multi-factor allocations is further analysed in Figure 1, Table 25 and Table 26 below.

In Figure 1 the graphs on the right hand side display the accumulated wealth (i.e. cumulative total index returns) since the beginning of the 40-year period for the SciBeta Long-Term US Multi-Beta Multi-Strategy (MBMS) EW together with its cap-weighted reference index in the top panel and the SciBeta Developed MBMS ERC and the SciBeta broad cap-weighted index in the bottom panel. On the left hand side, the graphs show the corresponding wealth ratio, i.e. the ratio of the wealth level of the MBMS index over the wealth level in the cap-weighted reference. If the wealth ratio goes up it means that the MBMS index is outperforming the cap-weighted index, and conversely if it goes down it is underperforming. We can see that over the 40-year US track record there was only one period where the MBMS EW index suffered relatively long underperformance, in the late 1990s. If one looks at the factor returns over this period, when there was the build-up of the technology bubble, the cap-weighted index performed quite well as it was quite concentrated in technology stocks. Of

Figure 1– Cumulative Index Returns and Wealth Ratio graphs - Plots on the right hand side show the value of a $1 investment in a Multi-Beta Multi-Strategy index and in its cap-weighted reference index. Plots on the left hand side display the ratio of the wealth accumulated by these respective investments. The analysis is based on daily total return data from 31 December 1972 to 31 December 2012 (40 years) using US Long-Term data in the top plots and from 31 December 2003 to 31 December 2013 (10 years) on the SciBeta Developed universe in bottom plots



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course over a short time period, it can happen that this concentration actually pays off relative to the factors used in the multi-beta allocation as large, high-beta and growth stocks fared better during that period than small, low risk or value stocks. Apart from that period when most of the factors did not pay off, the performance was quite steady over time. Similarly, one can link the periods of relative drawdown in the last 10 years in the Developed universe to short time spans where the factors happened not to work. However, as the multi-beta allocations diversify the sources of return, such periods are rare and relatively short.

Bearing in mind that the rewarded factors yield positive premia in the long term in exchange for risks that can lead to considerable underperformance or relative drawdowns in shorter periods, it is important to analyse the robustness of the performance and its dependence on the market and economic conditions. One approach is to use the National Bureau of Economic Research (NBER) definition of business cycles[54] to break down the analysis into alternating sub-periods of 'contraction' and 'expansion' phases. Table 29 shows annualised excess returns of the four Multi-Strategy factor indices over the broad CW index throughout different economic cycles. The Mid-Cap Multi-Strategy index has outperformed by a larger margin in expansion phases while the Low Volatility Multi-Strategy index has a bias towards contraction phases. The difference across each Multi-Strategy factor index can be big and presents opportunities for diversification across factors. The multi-beta allocations present less extreme variations throughout the different economic phases as they exploit the asynchronous movements of the different smart factor indices.

Furthermore, market conditions such as bullish or bearish markets may have a substantial impact on how different portfolio strategies perform. Amenc, Goltz and Lodh (2012) show considerable variation in the performance of some popular smart beta strategies in different sub-periods, revealing the pitfalls of aggregate performance analysis based on long periods. Separating bull and bear market periods to evaluate performance has been proposed by various authors such as Levy (1974), Turner, Starz and Nelson (1989) and Faber (2007). Ferson and Qian (2004) note that an unconditional evaluation made for example during bearish markets will not be a meaningful estimation of forward performance if the next period was to be bullish. We thus divide the 40-year period into two regimes: quarters with positive return for the broad CW index comprise bull market periods and the rest constitute bear markets. Table 29 shows that the performance of Multi-Strategy factor indices depends on market conditions. For example, the US Long-Term Mid-Cap Multi-Strategy index posts much higher outperformance in bull markets (+5.37%) than in bear markets (+3.02%). The opposite is true for the US Long-Term Low Volatility Multi-Strategy index, which underperforms by 0.81% in bull markets and outperforms by 7.33% in bear markets. If one combines the individual factor tilts, the dependency on the market regime is reduced for the multi-beta allocations compared to the constituent indices. Indeed, in terms of information ratio, the performance of the multi-beta allocations is roughly the same between bull and bear markets. In terms of returns, both the EW and ERC Multi-Beta allocations remain defensive diversification strategies, as they outperform by a larger amount in bear regimes than in bull markets.

54 - The NBER defines a recession as "a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales". See: http://www.nber.org/cycles/cyclesmain.html

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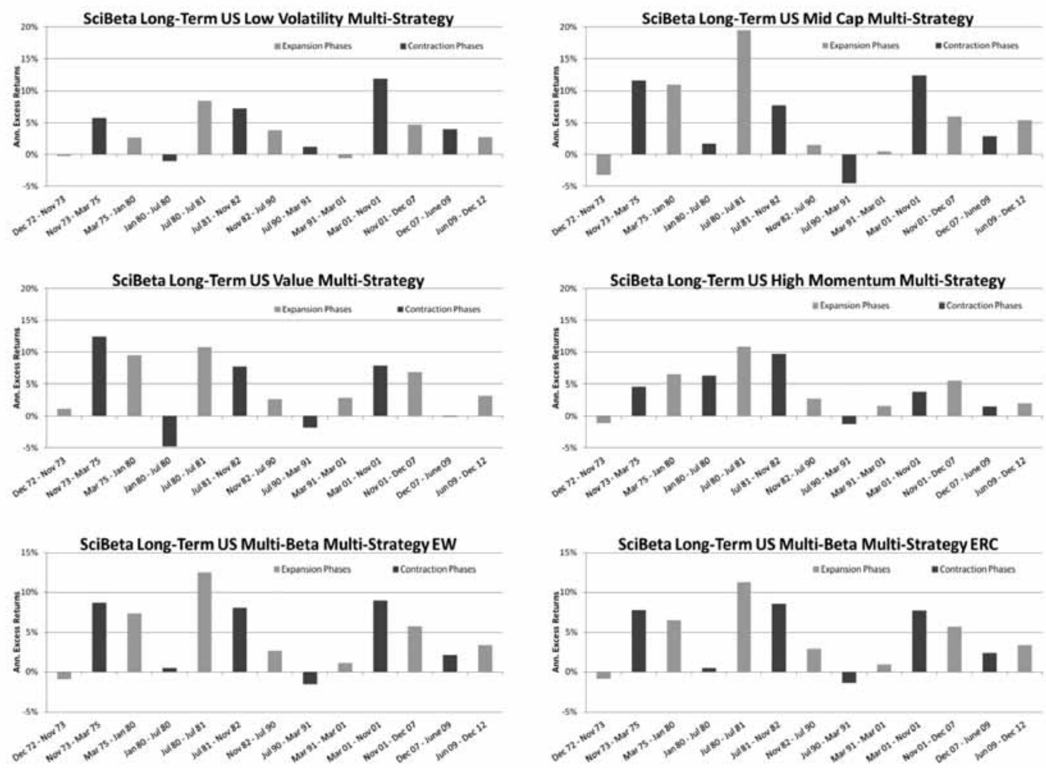
Table 25: Performance of Multi-Beta Multi-Strategy Allocations vs Single-Factor Tilts across Business Cycles - The table shows in Panel A the EW and ERC Multi-Beta allocations overall relative performance in contraction and expansion phases of the US economy (NBER) and the phase by phase detail of relative performance of Multi-Strategy Factor Indices for four factor tilts – mid-cap, high momentum, low volatility, and value, as well as the EW and ERC Multi-Beta allocations in contraction and expansion phases of the US economy (NBER). Complete stock universe consists of 500 largest stocks in the USA. The benchmark is the cap-weighted portfolio of the full universe. All statistics are annualised. The analysis is based on daily total returns from 31/12/1972 to 31/12/2012 (40 years).

Panel A

US Long-Term Track Records (Dec 1972 – Dec 2012)	Contraction Periods		Expansion Periods	
	EW MBMS	ERC MBMS	EW MBMS	ERC MBMS
Annual Relative Return	5.18%	5.00%	3.72%	3.53%
Information Ratio	0.75	0.75	0.76	0.78

Panel B



In the end, the multi-beta allocations on the smart factor indices allow the premia from multiple sources to be harvested while producing more effective diversification, as they achieve a smoother outperformance across the economic cycles and bull/bear market regimes.

4.3. Implementation Benefits of Allocating Across Factors

The multi-beta indices analysed above were designed not only to provide efficient management of risk and return but also for genuine investability. Each of the smart factor indices has a target of 30% annual one-way turnover which is set through optimal control of rebalancing (with the notable exception of the momentum tilt, which has a minimal target of 60% turnover). In addition, the stock selections

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Table 26: Conditional Performance of Multi-Beta Multi-Strategy Allocations and Single-Factor Tilts – The table shows relative performance of Multi-Strategy Factor Indices for four factor tilts – mid-cap, high momentum, low volatility, and value as well as the Multi-Beta EW and ERC allocations on these tilts in two distinct market conditions – bull markets and bear markets. Calendar quarters with positive market index returns comprise bull markets and the rest constitute bear markets. All statistics are annualised. The analysis is based on daily total return data from 31-December 1972 to 31 December 2012 (40 years) in panel A and from 31-December-2003 to 31-December-2013 (10 years) in panel B. Complete stock universe consists of 500 largest stocks in the USA (Panel A) and the 2000 stocks that form the SciBeta Developed universe. The benchmark is the cap-weighted portfolio of the full universe.

Panel A

US Long-Term Track Records (Dec 1972 – Dec 2012)	Diversified Multi-Strategy					
	Mid-Cap	Momentum	Low Vol.	Value	Multi-Beta EW Allocation	Multi-Beta ERC Allocation
Bull Markets						
Ann. Rel. Returns	5.37%	3.44%	-0.81%	3.89%	3.03%	2.88%
Ann. Tracking Error	5.86%	4.10%	5.17%	5.08%	4.45%	4.20%
Information Ratio	0.92	0.84	-0.16	0.77	0.68	0.69
Bear Markets						
Ann. Rel. Returns	3.02%	3.43%	7.33%	5.33%	4.83%	4.53%
Ann. Tracking Error	8.41%	6.20%	7.84%	7.10%	6.57%	6.11%
Information Ratio	0.36	0.55	0.93	0.75	0.74	0.74

Panel B

SciBeta Investable Developed Indices (Dec 2003 – Dec 2013)	Diversified Multi-Strategy					
	Mid-Cap	Momentum	Low Vol.	Value	Multi-Beta EW Allocation	Multi-Beta ERC Allocation
Bull Markets						
Ann. Rel. Returns	1.65%	1.70%	-1.76%	2.65%	1.07%	1.32%
Ann. Tracking Error	2.71%	3.06%	3.57%	1.97%	2.20%	1.93%
Information Ratio	0.61	0.56	-0.49	1.34	0.49	0.68
Bear Markets						
Ann. Rel. Returns	3.72%	3.31%	8.68%	1.87%	4.41%	3.93%
Ann. Tracking Error	4.45%	4.88%	5.87%	3.04%	3.47%	3.27%
Information Ratio	0.84	0.68	1.48	0.62	1.27	1.20

used to tilt the indices implement buffer rules in order to reduce unproductive turnover due to small changes in stock characteristics. The component indices also apply weight and trading constraints relative to market-cap weights so as to ensure high capacity. Finally, these indices offer an optional high liquidity feature which allows investors to reduce the application of the smart factor index methodology to the most liquid stocks in the reference universe. Amenc *et al.* (2014) present a more detailed explanation on how including carefully designed rules at different stages of the index design process eases implementation of investments in smart beta indices.

In addition to these implementation rules, which are applied at the level of each smart factor index, the multi-beta allocations provide a reduction in turnover (and hence of transaction costs) compared to a

4. Portfolio Construction Across Alternative Equity Beta Strategies

separate investment in each of the smart factor indices. This reduction in turnover arises from different sources. First, when the renewal of the underlying stock selections takes place, it can happen that a stock being dropped from the universe of one smart factor index is being simultaneously added to the universe of another smart factor index. Second, for constituents that are common to several smart factor indices, the trades to rebalance the weight of a stock in the different indices to the respective target weight may partly offset each other.

Table 27 displays statistics relative to the investability of the multi-beta equal-weight and relative ERC allocations along with the average of the mid-cap, momentum, low volatility and value smart factor indices. For comparison, we also show the same analytics for their Highly Liquid counterparts. We see that the turnover of multi-beta indices is very reasonable. In fact, managing a mandate on each smart factor index separately would yield a turnover which is higher than the average turnover across the smart factor indices. This is due to the fact that rebalancing each component index to the allocation target would induce extra turnover. However, implementing the multi-beta index in a single mandate exploits the benefits of natural crossing arising across the different component indices and actually reduces the turnover

Table 27- Implementation of Multi-Beta Allocations across Standard or Highly Liquid Factor-Tilted Indices The analysis is based on daily total return data from 31-December 1972 to 31 December 2012 (40 years) in panel A and from 31-December-2003 to 31-December-2013 (10 years) in panel B. The S&P 500 index and SciBeta Developed CW index are used respectively as the cap-weighted reference for US Long-Term Track Records and SciBeta Developed Investable Indices. Days to Trade is the number of days necessary to trade the total stock positions, assuming a USD1bn AUM and that 100% of the Average Daily Dollar Traded Volume can be traded every day. The weighted average market capitalisation of index is in $million and averaged over the 40-year period. All statistics are average values across 160 quarters (40 years). The net returns are the relative returns over the cap-weighted benchmark net of transaction costs. Two levels of transaction costs are used - 20 bps per 100% 1-Way turnover and 100 bps per 100% 1-Way turnover. The first case corresponds to the worst case observed historically for the large and mid-cap universe of our indices while the second case assumes 80% reduction in market liquidity and a corresponding increase in transaction costs. The risk-free rate is the return of the 3-month US Treasury Bill. (*)Due to data availability, the period is restricted to last 10 years of the sample for Scientific Beta US indices. Source: scientificbeta.com.

Panel A

US Long-Term Track Records (Dec 1972 – Dec 2012)	Diversified Multi-Strategy					
	All Stocks			High Liquidity Stocks		
	Average of 4 Smart Factor Indices	EW Multi-Beta	ERC Multi-Beta	Average of 4 Smart Factor Indices	EW Multi-Beta	ERC Multi-Beta
1-Way Turnover	34.19%	28.94%	31.53%	38.00%	33.21%	36.78%
Internally Crossed Turnover	-	5.65%	7.55%	-	5.53%	7.63%
Days to Trade for $1bn Initial Investment (Quantile 95%)(*)	0.20	0.12	0.12	0.16	0.07	0.07
Weighted Avg. Market Cap ($m)	9 378	9 378	10 280	13 295	13 295	15 283
Information Ratio	0.67	0.76	0.77	0.59	0.79	0.80
Relative Returns	3.90%	3.98%	3.79%	3.32%	3.43%	3.04%
Relative Returns net of 20 bps transaction costs (historical worst case)	3.84%	3.92%	3.73%	3.24%	3.37%	2.96%
Relative Returns net of 100 bps transaction costs (extreme liquidity stress scenario)	3.56%	3.69%	3.47%	2.94%	3.10%	2.67%

4. Portfolio Construction Across Alternative Equity Beta Strategies

Panel B

SciBeta Investable Developed Indices (Dec 2003 – Dec 2013)	Diversified Multi-Strategy					
	All Stocks			High Liquidity Stocks		
	Average of 4 Smart Factor Indices	EW Multi-Beta	ERC Multi-Beta	Average of 4 Smart Factor Indices	EW Multi-Beta	ERC Multi-Beta
1-Way Turnover	45.69%	39.63%	38.59%	45.85%	39.83%	38.36%
Internally Crossed Turnover	-	6.22%	7.76%	-	6.27%	8.12%
Days To Trade for $1bn Initial Investment (Quantile 95%)	0.48	0.27	0.27	0.20	0.09	0.09
Weighted Avg. Market Cap ($m)	16 047	16 047	16 493	22 391	22 391	23 737
Information Ratio	0.78	0.98	1.05	0.68	1.12	1.22
Relative Returns	2.57%	2.61%	2.55%	2.35%	2.40%	2.38%
Relative Returns net of 20 bps transaction costs (historical worst case)	2.48%	2.53%	2.47%	2.25%	2.32%	2.31%
Relative Returns net of 100 bps transaction costs (extreme liquidity stress scenario)	2.11%	2.21%	2.16%	1.89%	2.00%	2.00%

below the average level observed for component indices. We provide in the table for each multi-beta allocation the amount of turnover that is internally crossed in multi-beta indices as compared to managing the same allocations separately. We see that about 6% turnover is internally crossed by the EW allocation and that the ERC allocation which tends to generate more turnover also exploits natural crossing effects more than the EW allocation (around 7.8% is crossed internally). These cancelling trades result in an average one-way annual turnover that can be even lower than for the EW allocation, as is the case in the Developed universe.

In addition to turnover, the table also shows the average capacity of the indices in terms of the weighted average market cap of stocks in the portfolio. This index capacity measure indicates very decent levels, with an average market cap of around US$10bn for the multi-beta index, while the highly liquid version further increases capacity to levels exceeding USD 15bn in the case of the US Long-Term Track Records. In the case of the Developed universe, the weighted average market caps are higher since the period under scrutiny is more recent (last 10 years) – around US$16.3bn for the standard indices and US$23bn for the highly liquid ones. In both regions, we provide an estimate of the time that would be necessary to set up an initial investment (i.e. full weights) of $1bn AUM in the indices, assuming that the average daily dollar traded volume can be traded (100% participation rate) and that the number of days required grows linearly with the fund size[55]. Overall this does highlight the ease of implementation of the multi-beta indices and the effectiveness of the high liquidity option. Indeed, the Days to Trade required for the initial investment on US indices are very manageable (about 0.12 days for the standard multi-beta indices, and 0.07 days with the highly liquid feature). Even in the Developed universe, the highly liquid multi-beta indices would require about 0.09 days of trading. In addition, one should keep

55 - The Days to Trade (DTT) measure is computed for all stocks at each rebalancing in the last 10 years (40 quarters). Based on the estimated DTT for all constituents of a given index, we can derive an estimate of the required days to trade for the index itself, by using, for example, extreme quantiles of the DTT distribution over time and constituents, such as the 95th percentile that we report.

4. Portfolio Construction Across Alternative Equity Beta Strategies

in mind that the number of days needed to rebalance the indices (i.e. trade the weight change rather than the full weight on each stock) would be much lower. Even though the excess return is reduced by a few basis points, which can be explained by a potential illiquidity premium, it should be noted that the highly liquid multi-beta indices do maintain the level of relative risk-adjusted performance (information ratio) of the standard multi-beta indices in the US case and it provides even stronger information ratios in the Developed universe. Finally, even when assuming unrealistically high levels of transaction costs, all the smart factor indices deliver strong outperformance (from 2% to 3.69%) net of costs in both regions. Compared to the average stand-alone investment in a smart factor index, the multi-beta indices almost always result in higher average returns net of costs due to the turnover reduction through natural crossing effects across its component smart factor indices.

4.4. Multi-Factor Allocation: Towards a New Source of Value Added in Investment Management

While in practice investors may select among various ways of combining smart factor indices in order to account for their investment beliefs, objectives and constraints, the cases of an equal-weighted allocation, and a (relative) equal risk contribution allocation to four smart factor indices seeking exposure to the main consensual factors (notably value, momentum, low volatility and size) provide evidence that the benefits of multi-factor allocations are sizable. In particular, exposure to various factors whose premia behave differently over time and across market conditions provides for smoother outperformance. Moreover, natural crossing benefits reduce turnover of multi-factor mandates relative to separate single-factor mandates. Investors and asset managers may thus be well advised to further explore the potential of multi-factor allocations in a variety of investment contexts.

Part II: Survey: Use of Smart Equity Beta Strategies and Perceptions of Investment Professionals

1. Methodology and Data

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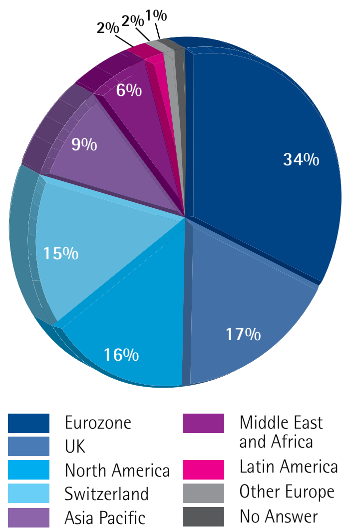
1.1 Methodology

The EDHEC Alternative Equity Beta Survey was carried out among a representative sample of investment professionals to identify their views and uses of alternative equity beta. This survey was taken with an online questionnaire and electronic mail. The questionnaire included about 25 questions that gathered in three main topics. A first group of questions was dedicated to evaluate the knowledge of respondents of the different types of alternative equity beta strategies and their area of usage of these strategies. A second group of questions was concerning the description of challenges facing by investors when using alternative equity beta. Finally, the third group of questions was about the importance of risk factors in alternative equity beta strategies.

1.2 Data

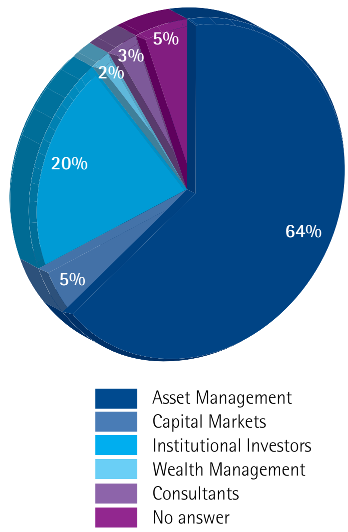
The email containing a link to the questionnaire was sent out at the beginning of 2014. The first response was received on the 2nd January 2014 and the last on the 3rd February 2014. In total we received 128 answers to our survey, covering the different parts of the world. However, European countries were dominant in the sample as two-thirds of respondents were based in Europe (half from Eurozone and half from the UK and Switzerland), while 16% were from North America and 17% from other parts of the world (9% from Asia Pacific, 6% from Middle East and Africa and 2% from Latin America). The exact breakdown of the respondents' countries can be seen in Exhibit 1.1.

Exhibit 1.1: Country distribution of respondents – This exhibit indicates the percentage of respondents that have their activity in each of the mentioned countries. Percentages are based on the 128 replies to the survey.



We also asked participants about their institution's principal activity. With about two-thirds of the survey participants, asset managers are the largest professional group represented in this study. 20% of respondents were institutional investors. The remainder of the sample is made up of professionals of capital markets (5%), wealth managers (2%) and consultants (3%).

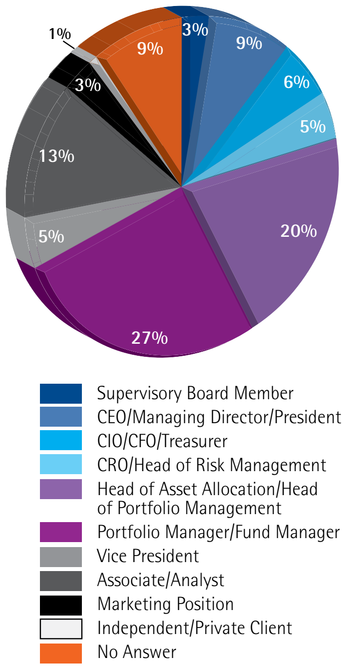
Exhibit 1.2: Main activity of respondents – This exhibit indicates the distribution of respondents according to their professional activities. Percentages are based on the 128 replies to the survey. Non-responses are reported as "no answer" so that the percentages for all categories add up to 100%.



1. Methodology and Data

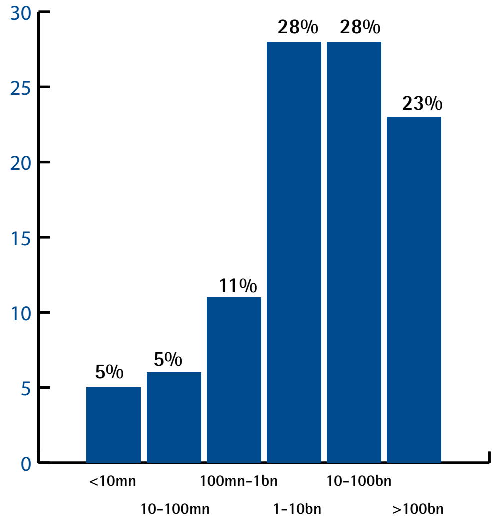
It is important to qualify respondents by their job function. Most respondents are key investment decision makers: 12% are board members and CEOs, 31% are directly responsible for the overall investments of their company (such as CIOs, CROs, or head of asset allocation or portfolio management) and 27% are portfolio or fund managers (see Exhibit 1.3).

Exhibit 1.3: Nature of respondent activity – This exhibit indicates the distribution of respondents based on their positions held in the company. Percentages are based on the 128 replies to the survey. Non-responses are reported as "no answer" so that the percentages for all categories add up to 100%.



Finally, Exhibit 1.4 shows the assets under management of the companies for which the survey respondents work. The responses were collected from 128 respondents that together have assets under management of at least €3.2 (USD 4.4) trillion. More than half (51%) of the firms in the group of respondents are large firms that have over €10bn in assets under management. Another 39% of respondents (i.e., more than one third of the respondents) are from medium-sized companies, with assets under management of between €100mn and €10bn. We also capture the opinions of small firms, with 11% having assets under management of less than €100mn. This feature on the size breakdown implies that the Alternative Equity Beta survey mainly reflects the views from medium to large-sized companies, with 90% of respondents.

Exhibit 1.4: Asset under management (€) – This exhibit indicates the distribution of respondents based on the assets under management in EURO or equivalent EURO which they reported. Non-responses were excluded.



Taken together, we believe that this regional diversity and fair balance of different asset management professionals make the survey largely representative of alternative equity beta users. After having described the sample that our survey is based on, we now turn to the analysis of the responses that we obtained from the group of survey participants.

1.3 Terminology

As a lot of different terms are currently used to refer to alternative equity beta strategies (cf. introduction), respondents were asked to indicate which ones they think were best describing these strategies. Results are displayed in Exhibit

1. Methodology and Data

1.5. It appears that there is no consensus on the appropriate term for describing alternative equity beta strategies, as none of the terms proposed reach a high score. On a scale from -2 (misleading/confusing term) to 2 (highly appropriate term), the highest score is for factor indices/factor investing with 0.66. However, respondents generally favour more neutral terms (e.g. "alternative" beta) to terms implying superiority of new types of beta (e.g. "prime" or "smart"). This is in line with oft-cited criticism of the term "smart beta"[56].

Exhibit 1.5: Terminology – Which overall term do you think best describes alternative equity beta strategies? Each term was rated on a scale from -2 (misleading / confusing term) to 2 (highly appropriate term).

Factor Indices / Factor Investing	0.66
Non-Cap-Weighted Indices	0.63
Alternative Beta	0.53
Systematic Investment Strategies	0.32
Strategy Indices	0.09
Smart Beta	0.04
Advanced Beta	-0.30
Beta +	-0.74
Beta prime	-0.88

56 - Cf. "Smart Beta: New generation of choices", IPE June 2012: http://www.ipe.com/smart-beta-new-generation-of-choices/45803.fullarticle; "Smart beta strategies: too clever by half?", Risk.net, April 2013: http://www.risk.net/structured-products/feature/2262579/smart-beta-strategies-too-clever-by-half.

2. Which Types of Alternative Equity Beta are Investors Using?

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2.1 What are the Reasons for Investing?

Respondents were first asked about their motivations for investing in alternative equity beta strategies. They were asked to rate a series of arguments from -2, if the proposition does not appear as an important argument for them to invest in alternative equity beta, to +2, if the argument correspondd to a strong motivation for them to invest in alternative equity beta. Results are displayed in Exhibit 2.1. It appears that the main arguments for respondents to use alternative equity beta strategies are to gain exposure to rewarded risk factors (average score of 1.22), as well as improving diversification relative to CW indices (average score of 1.13) (cf. Amenc, Goltz, Lodh, 2012; Amenc, Goltz, Lodh and Martellini, 2014b). These two arguments correspond to the main criticisms of cap-weighted indices (cf. Section 1.1 in Part I), namely the ignorance of other risk factors than the market factor and the lack of diversification. It is noteworthy that diversification is seen as being as important as factor exposures. This contradicts a widely held view that smart beta is nothing but delivering factor exposures (cf. Hsu, 2013).

Respondents do not see the reproduction of active management results as a main motivation for using such strategies.

Exhibit 2.1: Please indicate your agreement with the following proposals on the usefulness of alternative equity beta strategies. – The agreement was given on a scale from -2 (strong disagreement) to +2 (strong agreement). This exhibit indicates the average score obtained for each argument.

Alternative equity beta strategies are useful…	Average score
… because they allow to gain exposure to rewarded risk factors in a strategic equity allocation context	**1.22**
… because they improve diversification or index construction relative to cap-weighted index	1.13
… because they allow to reproduce the performance of active management through long-only systematic factor investing	0.18
… because they allow to replicate the performance of hedge funds through long/short factor investing	-0.26

In order to test the robustness of the answers given by respondents to this survey, we also considered them by category of respondents according to their activity (cf. Exhibit 1.2), their country (cf. Exhibit 1.1) and the size of the company (see Exhibit 1.4). It appears that whatever the category respondents belong to, we obtain similar results, proving that our results are quite robust, as they are not related to a specific category of respondents. Detailed results are provided in appendix C (see Exhibit C.1).

Respondents were then asked about the factors that have led them to adopt alternative equity beta strategies. They were proposed a list of six criteria including diversification, potential for lower risk than cap-weighted indices, potential for higher returns than cap-weighted indices, and the ability of advanced beta indices to provide reliable factor exposures, transparency and low cost. In addition, respondents may propose additional factors that seem important to them. Results are displayed in Exhibit 2.2. It appears that respondents use alternative equity beta strategies first of all for their

2. Which Types of Alternative Equity Beta are Investors Using?

diversification power, as well as for their ability to provide lower risk. Diversification and risk reduction are more important for them than the potential to obtain higher returns than cap-weighted indices.

Note that all of the criteria we listed are seen as highly important. The high importance attributed to transparency and low cost is at odds with product providers' practices of packaging smart beta as actively managed quant strategies which charge high fees and/or do not fully disclose the methodology. In addition to the list of factors proposed, respondents could also indicate if there were other factors that seem important to them. While about 20% of respondents indicate the existence of other factors, only four of them explicitly give the additional factor that led them to adopt alternative equity beta strategies. Their additional motivations to adopt alternative equity beta strategies are replacing underperforming active managers, to obtain a better Sharpe ratio, to obtain capital protection, to implement current strategies on a systematic basis and with less cost. Not surprisingly, respondents that explicitly name the factor give it a high impact (average score of 4.75), while those who do not explicitly name the factor give it a lower impact (average score of 2.43).

Exhibit 2.2 – What are the factors that have led you to adopt alternative equity beta strategies? –The strength of the impact associated with each aspect was rated from 1 (weak motivation) to 5 (strong motivation). This exhibit gives the average score obtained for each argument.

Diversification	3.78
The potential for lower risk than CW indices	3.74
The potential for higher returns than CW indices	3.50
Reliable factor exposures of advanced beta indices	3.20
Transparency	3.07
Low cost	3.04
Other, please specify	2.78

We provide in the appendix a test of robustness of these results by displaying them by category of respondents (see Exhibit C.2).

As cap-weighted indices remain the reference for a vast majority of investors, respondents were also asked their opinion about the role of cap-weighted indices in a context of alternative equity beta investing. Results indicate, as expected, that cap-weighted indices primarily serve ex-post to assess the performance of alternative equity beta strategies. Detailed results are provided in appendix B (cf. Exhibit B.1). Similarly, respondents were asked their opinion about the role of alternative equity beta strategies. It appears that respondents mainly see alternative equity beta strategies as a complement to standard equity indices, as well as a complement to long-only managers. Detailed results are provided in appendix B (cf. Exhibit B.2).

2.2 What are the Well-Known and Widely Used Strategies?

After being questioned about their reasons for investing in alternative equity beta strategies, respondents were asked about their familiarity with alternative equity beta strategies. A complete description of the common equity risk factors on which long-only strategies are based is to be found in Section 2.1 of Part I, while Section 2.2.1 of Part I presents standard long/short factors. Indeed, the respondent's relative knowledge of the various strategies will determine their investment in such products. A list of strategies was proposed to respondents including long-only and long/short strategies and they were invited to rate them from -2, if they were unfamiliar with them, to +2, if they were very familiar with the strategies. Results are displayed in Exhibit 2.3.

2. Which Types of Alternative Equity Beta are Investors Using?

It appears that respondents are much more familiar with long-only than with long/short strategies. Among long-only strategies, Low Volatility, Equal-Weighted and Value Strategies have the highest familiarity. Not surprisingly, the strategies that obtain the higher rate of familiarity are those based on popular factor premia largely documented in the literature for a long time (value, low volatility) or based on naïve weighting, such as equal-weighting. Decorrelation/diversification strategies have the lowest familiarity, among long-only strategies, even lower than some long/short strategies.

We provide in the appendix a test of robustness of these results by displaying them by category of respondents (see Exhibit C.3.a, for long-only strategies and Exhibit C.3.b for long/short strategies).

Respondents were then invited to indicate in which strategies they were investing among this list. Results are displayed in Exhibit 2.4. It appears that investment is strongly related to familiarity with the strategies. For long-only strategies, 61% of respondents invest in-low-volatility and value strategies, and 52% of respondents invest in fundamental-weighted strategies, which were the strategies investors were the most familiar with. However, only 31% of respondents invest in the equal-weighted strategy, a naïve strategy, though they are very familiar with it. Respondents also indicate that they are bound to increase their investments in all the strategies, but especially in those they are the most familiar with. Respectively 46%, 45% and 38% of respondents planned to increase their investment in low volatility, value and fundamental-weighted strategies.

Some strategies appear to have potential for development in the future, as for example decorrelation approaches. While only 23% of respondents already invest in this type of strategy, another 22% of respondents are currently examining a possible investment in the strategy.

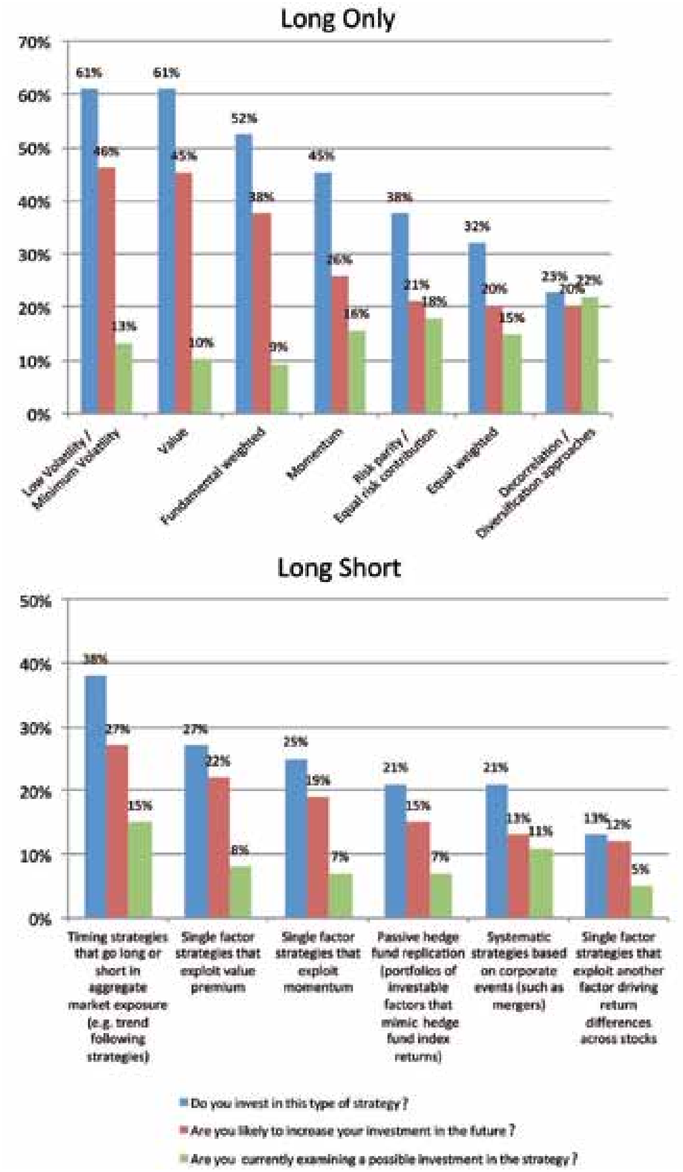
Concerning long/short strategies, while the percentages of respondents that already invest in them are lower, they also planned further development of their investment.

Exhibit 2.3: Which alternative equity beta strategies are you familiar with? – This exhibit gives the average score obtained for each strategy. The average score was obtained by averaging the familiarity score of five criteria (construction principles, implementation, long-term outperformance, drivers of outperformance, underlying risks) rated from -2 (do not know about the topic) to +2 (very familiar).

Long Only strategies	Average score	Long/Short Srategies	Average Score
Value	**1.16**	Timing strategies that go long or short in aggegate market exposure (e.g. trendfollowing strategies)	**0.54**
Low Volatility/Minimum Volatility	1.15	Single factor strategies that exploit value premium	0.46
Equal weighted	1.15	Single factor strategies that exploit momentum	0.45
Fundamental weighted	1.06	Single factor strategies that exploit another factor driving return differences across stocks	0.39
Momentum	0.93	Passive hedge fund replication (portfolios of investable factors that mimick hedge fund index returns)	0.21
Risk parity/Equal risk contribution	0.85	Systematic strategies based on corporate events (such as mergers)	0.19
Decorrelation/Diversification approaches	0.40		

2. Which Types of Alternative Equity Beta are Investors Using?

Exhibit 2.4: Concerning your own investment in these types of strategies, please indicate for each of the following strategies your current status? – For each of the strategies this exhibit indicates the percentage of respondents that already invest in it, together with the percentage of respondents that are likely to increase their investment in the future. It also shows the percentage of respondents that do not invest in the strategy at the present time, but consider a possible investment in the future.



2.3 Satisfaction Rates

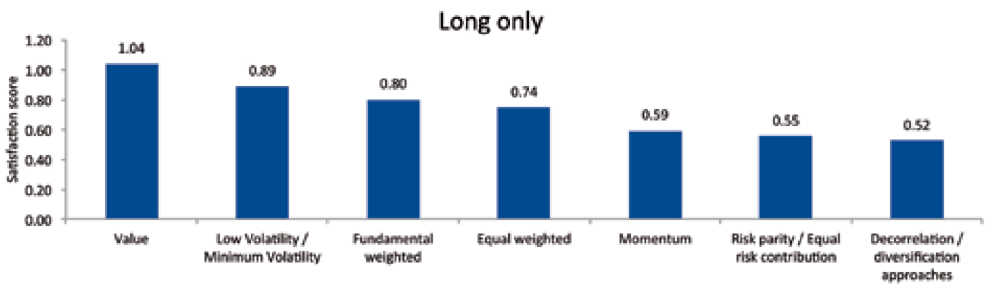
Respondents were then asked about their satisfaction level concerning the current offerings for each of the smart beta strategy they declare investing in, depending on their answers to the question displayed in Exhibit 2.4. Thus the 128 respondents of the sample were not all asked to give their opinion about the complete list of the strategies and the sample of respondents was a bit larger for long-only strategies than for long/short strategies, as smart beta long-only strategies are more largely used and known than long-only strategies. The satisfaction was rated from -2 (not at all satisfied) to +2 (highly satisfied). As shown in Exhibit 2.5, all strategies, whether they are long-only or long/short strategies received on average a positive

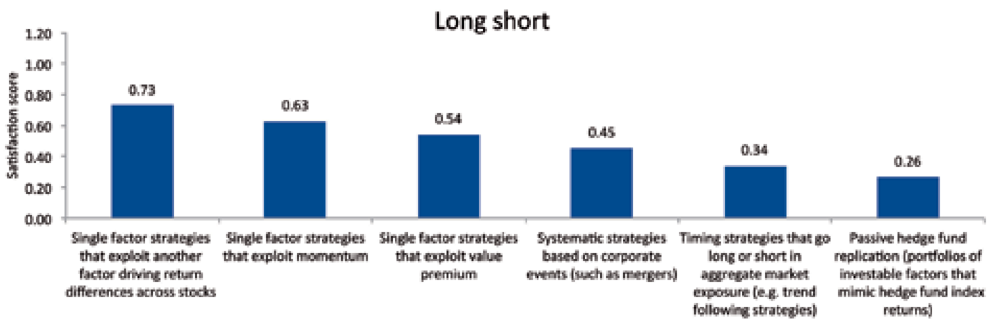
2. Which Types of Alternative Equity Beta are Investors Using?

rate of satisfaction from the respondents that already use them. It also appears that higher satisfaction rates are obtained for long-only strategies, than long/short strategies. The best satisfaction score was attributed to the Value strategy offering (1.04).

Concerning long-only strategies the satisfaction rate appears to be quite correlated with the familiarity with strategies, as the higher rates of satisfaction are attributed to the strategies respondents are the most familiar with. Concerning long/short strategies the results are a bit different. For example, timing strategies were the ones respondents were the most familiar with, but their rate of satisfaction of these strategies is one of the lowest among long/short strategies.

Exhibit 2.5: Please indicate your satisfaction level with the following offerings – The satisfaction was rated from -2 (not at all satisfied) to +2 (highly satisfied). Only categories that respondent invests in according to their previous answers (see Exhibit 2.4) were displayed. This exhibit gives the average score obtained for each strategy.





3. Challenges Facing Investors

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3. Challenges Facing Investors

After investigating the motivations for respondents to invest in alternative equity beta strategies, a second group of questions in this survey concerned the challenges investors were facing when they wanted to invest in alternative equity beta strategies. The main challenges are related to the familiarity with the strategies as well as to the strategy evaluation process in terms of performance and risk.

Initially, respondents were asked to rate the factors that prevent them from investing more in alternative equity beta strategies among a list of propositions. The results are displayed in Exhibit 3.1. It appears that respondents have the most concerns about robustness of alternative equity beta strategy performance. This hurdle is rated 3.62, on average, on a scale from 1 (weak hurdle) to 5 (strong hurdle). This resonates with widespread criticism echoed in the media and in the industry on potential robustness issues. Here are some examples of citations collected in recent professional publications: "The historical tests that do not predict the future for smart beta strategies" (Financial News, May 2014); "Market conditions … may present a headwind or tailwind for certain strategies. For example, compressed valuation spreads may present a more challenging environment for a value strategy" (Towers Watson, 2014); "… benchmarks are often being chosen for new products based on their attractive performance history. And, of course, past performance is no guarantee of future results" (Buckley, May 2013); "But is there real investment merit in these new indices? Or are they simply the product of data mining?" (Morningstar, November 2013); "Some alternative indices add value, but not necessarily under the same market conditions, investors need to understand the underlying biases and the overall fit in their portfolio before selecting the right benchmark" (Northern Trust, June 2012). See also Section 2.1.1.2 in this document for a literature review on the controversy of size effect robustness and Section 2.1.4.2 for a discussion on the robustness of the volatility effect. Implementation and transparency issues are also seen as important hurdles, with hurdles rated from 3.23 to 2.60, respectively (cf. sections 2.3.5 and 3.5 of part 1 for a discussion about turnover costs of dynamic factor strategies and diversification strategy indices, respectively). This resonates with the discussion around the need for transparency and poor industry practices in the area of transparency, especially for alternative beta indices. A recent survey of European investors (cf. Amenc and Ducoulombier, 2014) already identified room for improvement in this area, as only about a third of respondents were very (4.6%) or somewhat satisfied (30.3%) with the current level of transparency in the indexing industry and investors were strongly demanding higher standards of index transparency.

In addition to finding a confirmation in our recent survey of the challenges with transparency and information on alternative equity beta indices, investors' response indicating "limited information on risk" as a key challenge also suggests that they are likely to require more education not only on the benefits but also on the risks of advanced beta investing. In particular, one of the key risks of any advanced beta equity strategy is the relative risk with respect to a cap-weighted reference index. It is often the case that investors maintain the cap-weighted index as a benchmark, which has the merit of macro-consistency and is well-understood by all stakeholders.

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In this context, advanced equity beta strategies can be regarded as a reliable cost-efficient substitute to expensive active managers, and the most relevant perspective is not an absolute return perspective, but a relative perspective with respect to the cap-weighted index. However, the relative risk of advance beta equity strategies is often not emphasised by providers, and perhaps not enough attention is given to implementing suitable methods to benefit from the outperformance potential of alternative beta strategies while controlling the relative risk with respect to standard cap-weighted benchmarks (also see Amenc et al. 2014c).

The insufficient number of offerings is at the end of the list of hurdles, with an average score of 2.40. This reflects the situation after an impressive amount of new product launch activity by index providers. As reported in Ducoulombier, Goltz, Le Sourd and Lodh (2014), since the launch of the first fundamental factor-weighted ETF in May 2000 (Fuhr and Kelly 2011), there have been quite a number of ETFs introduced to track non-market-cap-weighted indices, including equal-weighted ETFs, minimum variance ETFs, characteristics-weighted ETFs, etc. According to CNBC[57], about 7% of ETF assets are linked to smart beta indices and such ETFs have seen 43% growth over 2013 compared to 16% growth over the overall ETF market. See Section 2.4 in Part I for a brief overview of equity index offerings from major index providers.

57 - "Smart beta: Beating the market with an index fund", CNBC, 7 November 2013, http://www.cnbc.com/id/101149598.

Exhibit 3.1: What do you think are factors that prevent you from investing more in alternative equity beta strategies? – The strength of the hurdles associated with each aspect was rated from 1 (weak hurdle) to 5 (strong hurdle).

Doubts over robustness of outperformance	3.62
Issues related to turnover and capacity	3.23
Limited information on risks	3.10
Limited availability of independent research	2.97
Limited availability of data	2.87
High licensing fees	2.82
Insufficient explanation of concepts behind offerings	2.76
Low transparency of rules	2.60
Insufficient number of offerings	2.40

3.1 Difficulties in Product Evaluation

3.1.1. Familiarity with Evaluation Process

Respondents were asked about their knowledge of the various aspects of smart beta strategies, including construction principles (see sections 2.3, 3.1 and 4 in part I for descriptions of construction of alternative beta strategies), implementation, long-term outperformance, drivers of outperformance and underlying risks. They were proposed to evaluate both long-only strategies and long/short strategies including Low Volatility / Minimum Volatility, Fundamental-weighted, Equal-weighted, Risk parity / Equal risk contribution, Decorrelation / diversification approaches, Momentum and Value for the long-only strategies and single-factor strategies that exploit value premium, single-factor strategies that exploit momentum, single-factor strategies that exploit another factor driving return differences across stocks, Passive hedge fund replication, Timing strategies, Systematic strategies based on corporate events for the long/short strategies. Exhibit 3.2a and 3.2b present the average score obtained for the various aspects of smart beta strategies for long-only and long/short strategies, respectively.

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First, it appears that all aspects obtain a higher score for long-only strategies than for long/strategies. Note that Exhibit 2.3 displayed in the previous section was based on the same sample of data, but displayed the average score obtained by strategy, instead of by aspect through all strategies. The present results are thus totally in accordance with those of Exhibit 2.3. Second, various aspects obtain a similar relative ranking both for long-only and long/short strategies. Investors are familiar with construction principles, with an average score of 1.26 for long-only strategies, but less familiar with underlying risks and drivers of performance, with an average score of 0.86 for both for long-only strategies. For long/short strategies, the average scores are, respectively, 0.56 for construction principles, 0.32 for underlying risks and 0.30 for drivers of outperformance.

A potential explanation is that providers do not offer a lot of information on performance drivers and risks. Amenc, Goltz and Martellini (2013) report that articles published by providers of given smart beta strategies often contain confusing statements about their competitors' strategies. For example, in an article published by promoters of fundamentals-based equity indexation in the *Financial Analysts Journal* (Chow, Hsu, Kalesnik and Little, 2011a), the authors, who highlight the importance of implementation rules to evaluate alternative equity indices, omitted to include the turnover management rules integrated by the competitors so

Exhibit 3.2 a – Long-only strategies: Which alternative equity beta strategies are you familiar with? For each alternative equity beta strategy, respondents were asked to rate each aspect including construction principles, implementation, long-term outperformance, drivers of outperformance, and underlying risks. The familiarity was rated from -2 (do not know about the topic) to +2 (very familiar). The exhibit displays the average score across all the strategies.

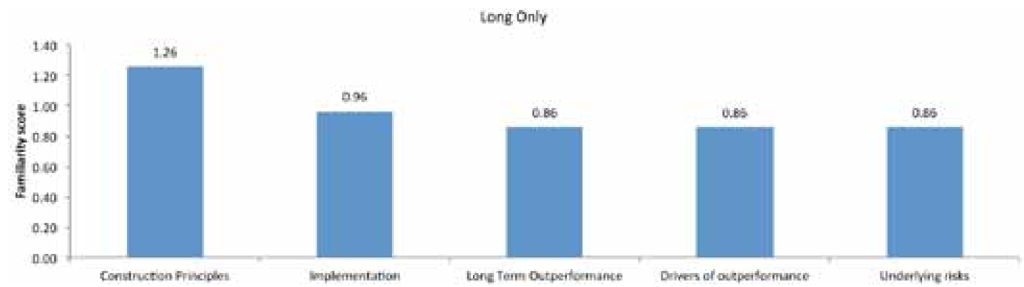
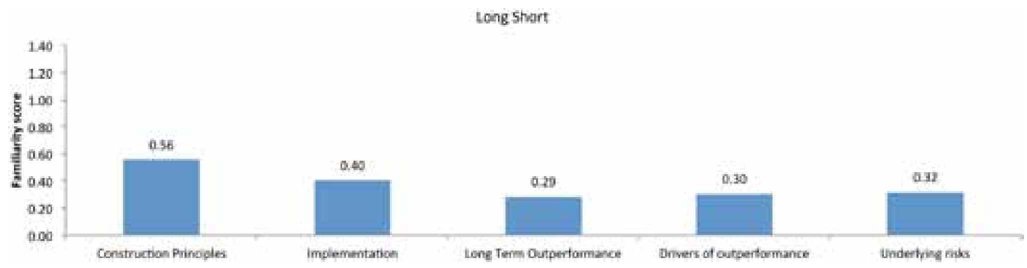


Exhibit 3.2 b – Long/Short strategies: Which alternative equity beta strategies are you familiar with? For each alternative equity beta strategy, respondents were asked to rate each aspect including construction principles, implementation, long-term outperformance, drivers of outperformance, and underlying risks. The familiarity was rated from -2 (do not know about the topic) to +2 (very familiar). The exhibit displayes the average score across all the strategies.



3. Challenges Facing Investors

as to then show that the turnover they calculated themselves for these strategies was higher than that of their own index (for more details on this issue, see Amenc, Goltz and Martellini, 2011, and Chow, Hsu, Kalesnik and Little, 2011b). In the same way, a recent article published in the *Journal of Indexes Europe* (Blitz, 2013), by promoters of low volatility strategies, asserts that Efficient Maximum Sharpe Ratio indices are exposed to higher volatility than cap-weighted indices over the long term, even though the article cited by the author to justify his argument (Clarke, de Silva & Thorley, 2013) does not specifically refer to Efficient MSR strategies. Moreover, this statement is inconsistent with an article published in the *Journal of Investment Management* (see Amenc, Goltz, Martellini and Retkowsky, 2011) analysing the performances and risks of this strategy which finds that the volatility of Efficient MSR is lower than that of a cap-weighted index containing the same stocks.

3.1.2 Resources for Evaluation Process

Respondents were then asked about the resources they employed for the evaluation of investment strategies and products within their organisation. The results are displayed in Exhibit 3.3. It appears that respondents allocate relatively few resources to evaluation of alternative beta. The average respondent uses fewer than two full-time staff to evaluate alternative beta offerings, a much lower number than used to evaluate active managers. The evaluation of advanced beta offerings is first of all based on the use of independent research, with a score of 3.32, and on use of analytic tools and research published by providers, with a score of 3.21 for both.

External consultants and meetings with providers are more frequently used for evaluating active managers than alternative beta offerings. On a scale from 0 to 5, respondents give on average a score of 1.08 for the use of external consultants for evaluating advanced beta offerings, versus 1.22 for evaluating active managers. Meetings with providers receive a score of 2.91 for evaluating advanced beta offerings, versus 3.29 for the evaluation of active managers.

These findings are not surprising as manager evaluation is a longstanding practice in the industry with established procedures while beta evaluation is less common as default choices (cap-weighted indices) have been used historically. On this subject, Amenc, Goltz, Lodh and

Exhibit 3.3: Concerning the criteria of evaluation of investment strategies and products within your organisation, please indicate the importance of the means of evaluation employed. The first column of the table displays an average number of staff, while the other five columns report a score given on a scale of 0 (if the means of evaluation is not used at all) to 5 (if the means of evaluation is used very frequently).

	Average number of full time staff mainly concerned with	Use of external consultants	Use of analytic tools	Meetings with providers	Use of research published by providers	Use of independent research
Evaluation of advanced beta offerings	1.77	1.08	3.21	2.91	3.21	**3.32**
Evaluation of cap-weighted indices and passive investment products	1.87	1.00	**3.10**	2.50	2.78	2.95
Evaluation of active managers	**3.42**	1.22	**3.19**	3.29	2.84	2.91

3. Challenges Facing Investors

Martellini, 2012) argue that managers are primarily evaluated on their performance relative to cap-weighted indices. If they manage their portfolios subject to relative risks, there is no systematic process in place to ensure that the relative risk that is due to generate over-performance is explicitly managed. However, the results of a survey by Northern Trust in 2011 and based on 121 respondents (cf. Northern Trust, 2012), reveal that more than 80% of respondents declare to be more concerned with meeting their own objectives than outperforming a traditional benchmark.

Concerning the average number of full -time staff, we provide in the appendix a test of robustness of these results by displaying them by category of respondents (see Exhibit C.4).

It is interesting to compare the results displayed in Exhibit 3.3 with those obtained in a recent survey published by Russell (cf. Russell, 2014). In the Russell survey it appears that asset managers are the primary source of information concerning smart beta strategies for more than half of respondents, both in North America and Europe (59% and 58% of respondents, respectively). North American asset owners are also quite numerous in relying on information from journal publications and index providers with 58% and 50% of respondents, while these are less numerous among European respondents (43% and 32%, respectively). Compared to our results, the use of external consultants appears of higher importance, as 46% of North American respondents and 43% of European respondents rely on them for credible information about smart beta strategies.

3.1.3 Challenges for Evaluation Process

3.1.3.1 Available Information

In order to compare the position of smart beta strategies with regards to other types of investments in terms of available information, respondents were then asked about the challenges they were confronted with when evaluating the various investment strategy offers including advanced beta offerings, cap-weighted indices and passive investment products and active managers. Results are displayed in Exhibit 3.4. It appears that respondents see bigger challenges with evaluating advanced beta offerings than with evaluating active managers or cap-weighted indexing products, as all the challenges except one (lack of transparency on methodology) receive a higher score, meaning they were seen as stronger problems for evaluating advanced beta offerings than evaluating active managers.

Lack of access to data (in particular live and after-cost performance, with scores of 3.63 and 3.34, respectively, on a scale from 1 to 5) and analytics is seen as a key challenge. The problem of index transparency is detailed in Ducoulombier (2013, 2014) and Amenc and Ducoulombier (2014). In new rules established by the European Securities and Markets Authority (ESMA) in July 2012 and applicable since February 2013 (ESMA/2012/832EN), ESMA prohibited the use of indices that do not disclose their "full calculation methodology" or fail to publish "their constituents together with their respective weightings." The regulator also required this information to be accessible easily and on a complimentary basis to investors and prospective investors. ESMA also prohibited investment in indices whose methodologies are not based on a set of pre-determined rules

3. Challenges Facing Investors

Exhibit 3.4: Concerning the challenges for evaluation of investment strategies and products, please indicate what you see as a challenge. Challenges were rated from 1 (weak challenge) to 5 (very strong challenge).

	Lack of transparency on methodology	Lack of access to data	Lack of availibility of live track records	Lack of after cost performance data	Lack of availibility of analytics	Lack of availibility of independent research	Mean
Evaluation of advanced beta offerings	3.03	**3.15**	**3.63**	**3.34**	**2.95**	**3.15**	**3.21**
Evaluation of cap-weighted indices and passive investment products	1.97	1.97	2.01	2.09	1.96	2.12	2.02
Evaluation of active managers	**3.20**	3.01	2.85	2.66	2.77	2.76	2.87

and objective criteria, or which permit the so-called "backfilling" of data.

We provide in the appendix a test of robustness of these results by displaying the average ratings of the various challenges by category of respondents (see Exhibit C.5).

3.1.3.2 Risk Evaluation

Besides the problem of data availability, the evaluation of the risks of the strategies is also a big challenge in the evaluation process. Respondents were thus asked to give their opinion about the importance of the various dimensions of risk they have to take into consideration in the evaluation process. These various dimensions of risk include the relative risk of underperforming cap-weighted indices, the systematic risk related to the factor tilts, the risks related to unrewarded risk factors and strategy-specific risk. The results are displayed in Exhibit 3.5. From this table it appears that for all types of risks, respondents agree that information is not widely available from product providers, as on a scale from -2 (information not widely available) to +2 (information widely available), the score is negative for three types of risks, and barely positive (0.04) for the fourth one (relative risk of underperforming cap-weighted indices). In terms of importance of risk, the strategy-specific risk is rated as the most important (1.12 on a scale from -2 to +2), closely followed by the systematic risk related to factor tilts (1.07). The relative risk of underperforming cap-weighted indices periodically is the least important risk for respondents (average score of 0.77), compared to other risks, a result in accordance with those of Northern Trust (2012) (see Section 3.1.2).

Exhibit 3.5: Please evaluate the relative importance of the various dimensions of risks in the assessment of alternative equity beta strategies. The evaluation was given from -2 (totally unimportant) to +2 (highly important). Respondents were also asked their opinion about the availability of information on each type of risk on a scale from -2 (strongly disagree that information is widely available) to +2 (strongly agree that information is widely available).

	This risk dimension is important	Information on this type of risk is widely available from product providers
Relative risk of underperforming cap-weighted indices periodically	0.77	**0.04**
Systematic risk related to the factor tilts to rewarded risk factors such as value and small-cap	1.07	-0.10
Risks related to unrewarded risk factors such as sector risks or credit risks etc.	0.96	-0.33
Strategy-specific risk	**1.12**	-0.26

3. Challenges Facing Investors

3.1.3.3 Selection of Criteria for Evaluating Strategies

Evaluation of smart beta strategies may be based on a collection of criteria including sound theory, performance, popularity as well as ease of implementation. Respondents were then asked to sort out the various assessment criteria available to them according to their importance. Results are displayed in Exhibit 3.6. It appears that costs and transparency are crucial for respondents to evaluate strategies. These criteria obtain a score of 1.26 and 1.15, respectively on a scale from -2 (not at all important) to +2 (very important). In addition, theoretical justification, with a score of 1.14, is about as important as live performance (score of 1.24).

This finding is in line with the importance attributed to economic explanations of performance of a strategy that has been highlighted by many authors (cf. Amenc, Goltz and Lodh, 2014, Ang, 2013). The background section in part I of this document fully detailed the different economic explanations for factor risk premia (cf. Section 2.1.1.4 for economic explanation of the size effect, Section 2.1.2.3. for economic rationale for the value factor, Section 2.1.3.3. for the explanation of the momentum risk premium, Section 2.1.4.3 for the low volatility factor and Section 2.1.5.5 for economic rationale for the illiquidity risk premium).

From Exhibit 3.6, it also appears that respondents estimate that providers differ greatly on the assessment criteria more often than not, especially in the areas of transparency and live performance.

In addition, respondents were asked about the performance metrics they use to assess alternative equity beta strategies. Detailed results are provided in appendix B (cf. Exhibit B.3) and show that the least sophisticated measures are those most frequently used by respondents, both in terms of performance and risk evaluation.

3.2 Implementation Problems

Besides the challenges related to the smart beta strategy evaluation process, the use of these strategies will be totally related to their ease of implementation. Thus, a group of questions submitted to respondents was related to the difficulties they may be confronted with when implementing those strategies.

Exhibit 3.6: Assessment criteria of alternative equity beta strategies. Please express your agreement with the following statements relating to the assessment criteria of alternative equity beta strategies from -2 (strongly disagree) to +2 (strongly agree).

	This dimension is important for my peers	Providers differ greatly on this aspect
Cost	1.26	0.83
Live performance	1.24	0.98
Transparency	1.15	1.09
Strategy based on sound theory	1.14	0.91
Long-term backtrack performance	0.89	0.71
Ease of implementation	0.88	0.80
AUM in same strategy of same provider	0.65	0.63
Brand of provider	0.54	0.55
Adoption by sophisticated peers of same strategy from same provider	0.38	0.31
Short-term recent performance	0.36	0.30

3. Challenges Facing Investors

Exhibit 3.7: Combination of alternative equity beta strategies. The respondents were asked to express their agreement with the following statements relating to the combination of alternative equity beta strategies on a scale from -2 (strongly disagree) to +2 (strongly agree).

	Advanced beta has strong potential in this area	Well-designed offerings for this use are widely available
Static combinations of alternative equity beta strategies to diversify across different types	0.84	-0.12
Tactical switching across alternative equity beta strategies to exploit predictability in strategy returns	0.55	-0.49
Tactical switching across CW and alternative equity beta to exploit predictability in strategy returns or tracking error	0.40	-0.55

3.2.1 Strategy Combinations: Big Potential but Few Solutions

First of all, as the performance of alternative equity beta strategies may be related to economic conditions, the possibility to be able to combine different strategies is of great interest in order to have more robust performance over time (see Section 4 in part I for a full description of portfolio construction across alternative equity beta strategies). Respondents were thus asked to give their opinion about the potential of such combinations of strategies. They were also asked to give their opinion about the offer currently available in this area. Results are displayed in Exhibit 3.7. While respondents tend to agree that advanced beta has strong diversification potential through various strategies, they also agree that well-designed offerings for this use are not widely available yet, which prevents them for using alternative beta strategies in this way.

These results are in line with a rich academic background (cf. Amenc, Goltz, Lodh and Martellini, 2012 as well as Kan and Zhou, 2007, for a discussion about combining portfolio strategies) to such an approach, but relatively few products available in this area. The recent launches of multi-strategy and multi-factor ETFs that occurred after this survey was done should be noted. For example, PowerShares launched a Multi-Strategy Alternative ETF in May 2014[58], Morgan Stanley launched in June 2014 an ETF based on the ERI Scientific Beta Developed Multi-Beta Multi-Strategy Equal-Weight Index. At the same time, Amundi was launching an ETF based on the ERI Scientific Beta Developed Multi-Beta Multi-Strategy ERC Index[59]. In July 2014, Advisor Shares was launching the Sunrise Global Multi-Strategy ETF[60].

We provide in an appendix a test of robustness of these results by displaying them by category of respondents (see Exhibit C.6).

3.2.2 Implementation Assessment

Respondents were then asked about the measures they use to assess implementation aspects of alternative equity beta strategies (cf. Section 4.3 in Part I for an illustration of implementation assessment of a multi-beta strategy). A list of measures to be rated from 0 to 5, whether they did not use it at all or frequently, was proposed. Results are displayed in Exhibit 3.8.

From this survey, it appears that implementation is a key aspect for respondents who commonly use a wide array of measures to assess implementation of alternative equity beta strategies, including turnover, trading

58 - https://www.invesco.com/static/us/investors/contentdetail?contentId=5f531bcd010c5410VgnVCM100000c2f1bf0aRCRD
59 - http://www.hedgeweek.com/2014/06/15/204814/morgan-stanley-and-amundi-unveil-ucits-etfs-based-eri-scientific-beta%E2%80%99s-smart-beta
60 - http://www.wdrb.com/story/25955216/launch-date-announced-for-advisorshares-sunrise-global-multi-strategy-etf-mult

3. Challenges Facing Investors

Exhibit 3.8: Implementation assessment. Which measures do you use to assess implementation aspects of alternative equity beta strategies? The importance of the measure was given on a scale from 0 (not used at all) to 5 (very frequently used).

Turnover	3.77
Trading volume	3.48
Average market cap of constituents	3.30
Bid / ask spreads	3.23
Market impact	3.22
Market conditions during which turnover occurs	2.98

volume, average market cap constituents, bid/ask spreads etc. This finding may be explained by the fact that transaction hurdles depend to a large degree on investors and their implementation capacity. Thus, there is a discussion in the literature on the transaction costs of some alternative beta strategies coming to sometimes very different results depending on assumptions about true transaction costs (cf. Section 2.3.5 in the background of this survey). In addition, the methodology to measure costs may be quite different depending on the studies and lead to different results (cf. Lesmond, Schill and Zhou, 2002; DeGroot, Huij and Zhou, 2011, for a review). Thus investors may be well advised to do their own analysis depending on their scale and setup.

This finding of challenges with implementation may also reflect that little information is available from alternative beta providers on implementation, how it can be facilitated and what implementation costs are. Implementation rules are not necessarily very transparent (see for example Arnott[61]'s discussion about RAFI emerging market index and the problem of free-float adjustment in back-tests). The index track records are not necessarily trustable as shown in Vanguard (2012), where a study of 370 U.S ETF benchmark indices show ssignificant differences between back-tested and live indices. While 300 indices were outperforming their benchmark during the back-test, only 189 outperformed after the live date, and the average performance fell from 10.31% to -0.91%.

61 - P. Amery. RAFI Corrects Statements on EM Backtests. March 18 2013. ETF.com.

3.2.3 Strategy Implementation: Long-Only versus Long/Short Strategies

Respondents were asked about their preference to gain exposure to alternative risk premia. Results are displayed in Exhibit 3.9. It appears that respondents prefer long-only strategies to gain exposure to alternative risk premia, in particular due to perceived implementation hurdles for long/short strategies. The differences in performance and risk between long/short and long-only strategies as perceived by respondents to gain exposure to risk premia appear to be less pronounced. This result is in accordance with the theoretical discussion provided in Section 2.3.1 in part I, namely that long-only strategies allow most of the profitability of alternative risk premia to be captured, and are often

Exhibit 3.9: Methodology choice. Which method do you prefer to gain exposure to alternative risk premia such as value, small-cap, etc. in the equity universe, on a scale from -2 (weakly prefer) to +2 (strongly prefer)?

	Ease of implementation	Regulatory framwork	Performance	Risk
Long/short strategies	0.35	0.09	0.65	0.60
Long only tilted strategies	**1.01**	**0.69**	**0.81**	**0.80**

3. Challenges Facing Investors

Exhibit 3.10 – Benefits and challenges of long/short strategies versus long-only strategies. Open answers.

Benefits of long/short strategies versus long only	Challenges of long/short strategies versus long only
Provide more opportunities and diversification and offer more potential in terms of factor exposure	Implementation challenges (skill, expertise, infrastructure) and lack of diversity in products available
Allow a better risk control and risk reduction (lower volatility, lower downside risk)	Lack of transparency and understanding
Improve risk-adjusted returns (Sharpe ratio)	Extreme risks and potential large losses
Are less costly	Regulatory issues and constraints
	Potential higher cost of shorting (turnover, transaction, costs)

better alternatives compared to long/short strategies for practical issues.

To complete this comparison of long / short versus long-only strategies, respondents were able to give open answers about how they see the main benefits and challenges of long/short approaches compared to long-only strategies. There was quite a consensus among the respondents and their answers may be gathered in the few assertions displayed in Exhibit 3.10. Respondents think that long/short strategies may possibly provide more opportunities and allow better risk-control, leading to better risk-adjusted returns. They also think that they may be less costly. However, respondents also mention the possibility of higher costs for long/short strategies compared to long-only in the list of challenges, as well as extreme risks and potential large losses.

3. Challenges Facing Investors

4. The Importance of Factors in Alternative Equity Beta Strategies

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The last group of questions in the survey concerned the factors inherent in the alternative equity beta strategies and how these factors explained the performance of the strategies. See Section 2.1 of the background for a review of common equity risk factors.

4.1 Factors as Performance Drivers

Respondents were asked their opinion about a list of assertions qualifying the performance of alternative equity beta strategies, compared to cap-weighted indices. Results are displayed in Exhibit 4.1. Among all propositions, the one that receives the highest score is that "the performance of alternative equity beta strategies is explained by factor tilts". Thus, factors are seen as the main performance driver of alternative beta. To a lesser extent, respondents also consider that the performance of alternative equity beta strategies is partly explained by rebalancing effects, as well as diversification. Respondents are less convinced that the performance of alternative equity beta strategies is the result of data mining. Interestingly, "factor investing" is the preferred label for these strategies (see Exhibit 1.5 in Section 1).

We provide in the appendix a test of robustness of these results by displaying them by category of respondents (see Exhibit C.7).

Respondents were then asked to indicate which factors were liable to be positively rewarded over the next ten years, after accounting for transaction costs and other implementation hurdles. Results are displayed in Exhibit 4.2. It appears that none of the five factors proposed to respondents obtained a poor score. On a scale from 0 (no confidence that the factor will be rewarded) to 5 (high confidence that the factor will be rewarded), the lowest score was obtained for the Momentum factor with 2.55. Value and Small-Cap are the two factors considered by respondents to be most likely to be rewarded, with a score of 3.28 and 2.93, respectively, which is not surprising as the existence of the value premium and small-cap premium has been largely developed in the literature for a long time.

Respondents were more specifically asked about their requirements to consider the selection of a given set of factors in their investment approach. They were proposed to rate a list of factors characteristics from 0, if the assertion was not important, to 5, if it was absolutely crucial. Results are displayed in Exhibit 4.3. It appears that all the characteristics proposed receive quite

Exhibit 4.1: Performance of alternative equity beta strategies. Please indicate your agreement/disagreement with the following statements regarding the performance of alternative equity beta strategies compared to cap-weighted indices in a range from -2 (totally disagree) to +2 (completely agree).

Statement	Agreement
The performance of alternative equity beta strategies is explained by factor tilts	1.04
The performance of alternative equity beta strategies is explained by rebalancing effects	0.39
The performance of alternative equity beta strategies is explained by the fact that they are less concentrated than cap-weighted indices	0.27
The performance of alternative equity beta strategies is explained by the fact that they exploit the magic of diversification and take into account the correlation across stocks	0.21
The performance of alternative equity beta strategies is explained by data mining	-0.20

4. The Importance of Factors in Alternative Equity Beta Strategies

Exhibit 4.2 – Rewarded factors. Which equity risk factors do you think will be rewarded positively over the next ten years, after accounting for transaction costs and other implementation hurdles? The level of confidence was rated from 0 (no confidence) to 5 (high confidence).

Value	3.28
Small-Cap	2.93
Low Volatility	2.68
Liquidity	2.65
Momentum	2.55

Exhibit 4.3: Requirements about factors. Which requirements do you have in order to consider a given set of factors in your investment approach from 0 (not important) to 5 (absolutely crucial)?

Factors should be easy to implement with low turnover and transaction cost	3.72
Factor premium should be related to a rational risk premium, i.e. explained by a substantial risk that the factor pays off badly in bad times	3.62
Factor premium should be documented in a vast empirical literature	3.42
Factor premium has been explained as an "anomaly" allowing rational agents to profit from irrationality of others	2.92
Factors should be related to firm fundamentals	2.78
Factors should be related to macroeconomic variables	2.47
Factors must be orthogonal	2.42

a high score. However, respondents are first concerned by ease of implementation and low turnover and transaction costs, with a score of 3.72, closely followed by a rational risk premium, with a score of 3.62.

4.2 Economic Explanations Matter

For the main alternative equity beta strategies, namely value, momentum, small-cap and low volatility, respondents were asked to give their opinion on the likely explanations of risk premia. Results are displayed in Exhibit 4.4. It appears that factor premia are mainly explained as compensation for risk (small-cap, value) or by behavioural biases of investors (value, momentum, low volatility). The small-cap premium is also related to liquidity risk.

We provide in the appendix a test of robustness of these results by displaying them by category of respondents (see Exhibit C.8).

Finally respondents were asked about the characteristics they consider to be important for a factor-tilted alternative equity beta strategy. Results are displayed in Exhibit 4.5. It appears that respondents require more from factor investing strategies than simply providing the right direction of exposure. It also seems important to them that the factor strategy provides the best ease of implementation, at a low implementation cost. Also important to them is that the strategy achieves the best possible reward for a given factor and that it provides exposure to the relevant risk factor, while maintaining neutral exposure to other risk factors.

At the same time, respondents were asked for each of these requirements if they think they were achieved by current products. Results are also displayed in Exhibit 4.5. It appears that current products are seen as insufficient for these requirements, the worst score being obtained by the ability

4. The Importance of Factors in Alternative Equity Beta Strategies

Exhibit 4.4: Explanation of factor premia. Which do you think is the most likely explanation for the value, small-cap, momentum and low volatility premium documented in the academic literature? Please indicate how important/credible the following interpretation is on scale from 0 (not at all credible) to 5 (highly credible)

Factor	Value premium	Momentum premium	Small cap premium	Low volatility premium
Explained as compensation for risk	3.27	2.26	**3.94**	2.25
Explained by behavourial biases of investors	**3.50**	**3.97**	3.27	**3.43**
Explained by many researchers examining the same data and identifying a pattern which is unlikely to persist in the future (data mining)	2.10	2.35	2.13	2.32
Related to macroeconomic risk factors	2.31	2.07	2.51	1.99
Related to liquidity risk	2.33	2.02	3.62	2.09
Related to distress risk	2.65	1.76	2.59	1.83

Exhibit 4.5: Requirements for alternative equity beta strategies. Which requirements do you consider to be important for a factor-tilted alternative equity beta strategy from -2 (not at all important) to +2 (important)? To which degree do you think currently available products fulfil each requirement from -2 (not fulfilled at all) to +2 (completely fulfilled). The last column displays open answers given by respondents as examples of suitable methods.

Property	Importance	Achievement by current products	Suitable methods
A factor strategy needs to provide the right direction of exposure, i.e. have the highest possible correlation with a factor	1.24	0.49	Technical trend analysis, regression, information coefficient, underlying risks, t-stat
A factor strategy needs to provide the best size, i.e. highest possible rewarded for a given factor, i.e. achieve the best possible reward for a given factor exposure	0.93	0.19	Market cap of target population, Sharpe ratio, underlying risks
A factor strategy needs to provide the best ease of implementation, i.e. implement a given factor tilt at low implementation cost	1.17	0.25	Customised strategy turnover, underlying risks
A factor strategy needs to hedge out undesired risk exposures, i.e. provide exposure to the relevant risk factor while maintaining neutral exposure to other risk factors	0.85	-0.13	Diversification, orthogonalisation methods, underlying risks

of current products to hedge undesired risk exposures.

Respondents were finally given the opportunity to propose examples of suitable methods for each of the requirements. Their answers are displayed in the last column of the table on Exhibit 4.5.

Appendix

Appendix

A. Construction Methodology of the Liquidity Factor of Pastor and Stambaugh (2003)

1. Construction Methodology of the Liquidity Measure:

Formally, the authors construct market illiquidity in a given month as the equally-weighted average of the illiquidity measure of individual stocks. The illiquidity measure is captured as follows:

$$r^e_{i,d+1,l} = a_{i,l} + \phi_{i,l} * r_{i,d,l} + \gamma_{i,l} * sign(r^e_{i,d,l}) * v_{i,d,l} + \epsilon_{i,d,l} \quad (9)$$

Where $r_{i,d,l}$ is the return of stock i on day d in month l, $r^e_{i,d,l}$ is the excess return (over CW) of stock i on day d in month l and $v_{i,d,l}$ is the dollar volume for stock i on day d in month l. $\hat{\gamma}_{i,l}$ is the illiquidity measure for stock i in month l. "$sign(r^e_{i,d,l}) * v_{i,d,l}$" represents the dollar volume signed by the contemporaneous excess return of the stock and it is a proxy of the order flow. The intuition is that the order flow should be accompanied by a return that should be partially reversed in the future if the stock is not liquid. In other words, $\gamma_{i,l}$ is expected to be negative when liquidity is lower. The "$sign(r^e_{i,d,l}) * v_{i,d,l}$" is used in order to remove market-wide shocks and better isolate the individual stock effect of volume related return reversals. The authors also include in the regression the lagged stock return $r_{i,d,l}$ as a second independent variable in order to capture return effects that are not volume related.

2. Portfolio Formation of the Illiquidity Factor-Tilted Portfolios:

We define β^L_i as the stock i sensitivity to innovations in aggregate liquidity L_t. Formally, it is defined as follows:

$$r_{i,t} = \beta^0_i + \boldsymbol{\beta^L_i} * L_t + \beta^M_i * MKT_t + \beta^S_i * SMB_t + \beta^H_i * HML_t + \epsilon_{i,t} \quad (10)$$

Where β^L_i captures the asset co-movement with innovations in aggregate liquidity. The authors allow β^L_i to be time-varying.

The "predicted" values of β^L_i, used to sort stocks, are obtained using two methods. In the first method, the "predicted" values of β^L_i depend on the stock's historical least-squares estimated (i.e. the estimate obtained from the regression (3)) and a number of additional stock characteristics (e.g. average value of $\hat{\gamma}_{i,l}$ from month t-6 through month t-1, the log of stock average dollar volume from month t-6 through month t-1, the cumulative return on the stock from month t-6 through month t-1, the standard deviation of the stock monthly return from month t-6 through month t-1, the log of the price per share from month t-1 and the log of the number of shares outstanding from month t-1). In the second method, the predicted values of β^L_i depend only on the stock's historical least-squares estimated and this is what the authors call the "historical" betas. Here we will only discuss the first method as the second method is a special case of the first one.

The portfolio formation begins with estimating $\gamma_{i,t}$ the liquidity sensitivity of each stock i at month t (i.e. regression (2)). In order to construct the innovations in aggregate liquidity L_t, the authors follow the following steps:

(1) Scale monthly differences in liquidity measures for each stock i (i.e. $\Delta\hat{\gamma}_{i,t} = \hat{\gamma}_{i,t} - \hat{\gamma}_{i,t-1}$) and average them across stocks in order

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to achieve $\Delta\hat{\gamma}_t$

(2) Regress

$$\Delta\hat{\gamma}_t = a + b\,\Delta\hat{\gamma}_{t-1} + c * ScaleFactor * + \hat{\gamma}_{t-1} + u_t \quad (1)$$

(3) Compute the innovations L_t as $L_t = \frac{1}{100} * \hat{u}_t$ (2)

(4) Model each stock "predicted" liquidity beta β_i^L as

$$\beta_{i,t-1}^L = \psi_{1,i} + \psi_{2,i}' * Z_{i,t-1} \quad (3)$$

where $Z_{i,t\text{-}1}$ is a vector containing the historical beta estimates (obtained from the regression (10)) and the six stock characteristics mentioned above.

(5) By placing equation (3) in equation (10), the authors obtain

$$r_{i,t} = \beta_i^0 + \beta_i^M * MKT_t + \beta_i^S * SMB_t + \beta_i^H * HML_t + (\psi_{1,i} + \psi_{2,i}' * Z_{i,t-1})L_t + \epsilon_{i,t} \quad (4)$$

(6) To restrict the coefficients to be the same across all stocks (equation (10)), the authors use the following regression

$$e_{i,t} = r_{i,t} - \hat{\beta}_i^M * MKT_t - \hat{\beta}_i^S * SMB_t - \hat{\beta}_i^H * HML_t \quad (5)$$

Where $\widehat{\beta's}$ are estimated using regression at point (2)

(7) Finally they run the following pooled time series cross-sectional regression to obtain the parameters used for sorting and ranking stocks.

$$e_{i,t} = \psi_0 + \psi_1 * L_t + \psi_2' * L_t + v_{i,t} \quad (6)$$

The estimated coefficients $\hat{\psi}_1$ and $\hat{\psi}_2$ are used in ranking the stocks.

B. Some Additional Questions

We present in this appendix some additional points respondents were also asked about.

1. Use of Cap-weighted Indices in the Context of Alternative Equity Beta Investing

Respondents were asked about their opinion on the role of cap-weighted indices in the context of alternative equity beta investing. Results are displayed in Exhibit B.1. According to them, cap-weighted indices primarily serve ex-post to assess the performance of alternative equity beta strategies (score of 1.02 on a scale from -2 to +2), rather than for controlling ex-ante the risk of deviating from cap-weighted indices (score of 0.43).

2. Use of Alternative Equity Beta Investing

Respondents were asked to give their opinion on the role of alternative equity beta strategies compared to standard equity indices, long-only and long/short managers. Results are displayed in Exhibit B.2. Respondents see alternative equity beta strategies as having potential as complements to standard equity indices (score of 0.94 on a scale from -2 to +2), as well as complements to long-only managers

Exhibit B.1: Role of cap-weighted indices. Please indicate the importance of the following use of cap-weighted indices in the context of alternative equity beta investing on a scale from – 2 (totally unimportant) to +2 (highly important).

CW indices remain the ultimate reference and are important in ex post performance assessment of alternative equity beta strategies	1.02
CW indices are important as an easily understandable external policy benchmark (e.g. used by trustees) while alternative beta strategies can be used as internal benchmarks (e.g. used by the asset manager)	0.76
CW indices allow to be managed the ex ante relative risk of deviating from CW indices when pursuing alternative equity beta strategies	0.43

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(score of 0.84). However, scores for uses of alternative beta strategies in this way are quite low (0.63 and 0.40, respectively), caused by a lack of well-designed offerings for this use.

3. Use of Performance Metrics to Assess Alternative Equity Beta Strategies

Respondents were asked about the performance metrics they use to assess alternative equity beta strategies, including absolute and relative measures of return and risk, as well as diversification metrics. Results are displayed in Exhibit B.3. It appears that the Sortino ratio and diversification metrics are the least used indicators to assess strategy performance. Respondents largely prefer the Sharpe ratio and information ratio or even average return. In terms of risk evaluation, relative downside risk measures are the least used, while volatility and maximum drawdown are the most frequently used measures.

Exhibit B.2: Use of alternative equity beta strategies. Please express your agreement from – 2 (strongly disagree) to +2 (strongly agree) with the following statements relating to the usage of alternative equity beta strategies.

	Advanced beta has strong potential in this area	I use advanced betas mainly in this way	Well designed offerings for this use are widely available
Alternative equity beta as a substitute to standard equity indices	0.37	-0.20	-0.14
Alternative equity beta as a complement to standard equity indices	**0.94**	**0.63**	**0.27**
Alternative equity beta as a substitute to active long only managers	0.57	0.04	-0.03
Alternative equity beta as a complement to active long only managers	0.84	0.40	0.23
Alternative equity beta as a substitute to active long short managers	-0.13	-0.47	-0.54
Alternative equity beta as a complement to active long short managers	0.17	-0.25	-0.28

Exhibit B.3: Performance metrics. Which performance metrics do you use to assess alternative equity beta strategies? Please indicate the importance of each of them on a scale from 0 (not used at all) to +5 (used very frequently).

Absolute performance	
Average return	3.65
Sharpe ratio	**3.98**
Sortino ratio	2.65
Relative performance	
Average excess return	**3.81**
Information ratio	3.77

Absolute risk	
Volatility	**4.18**
Downside risk such as semi deviation or VaR	3.62
Max DD	4.09
Relative risk	
Tracking error	**3.58**
Downside risk such as relative semi deviation or VaTeR	2.57
Max relative DD	3.20

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Diversification metrics	
Concentration indicator such as Herfindahl index or effective number of stocks	2.41
Diversification indicator such as diversification or average correlation or effective number of bets	**2.47**

C. Robustness

In order to test the robustness of the answers given by respondents in this survey, the main results were also considered by category of respondents. Three partitions were used.

a. Asset managers versus institutional investors

b. Equity oriented countries[62] versus other countries[63]

c. Companies having an amount of assets under management < 10bn versus companies having an amount of asset under management ≥ 10bn.

Results are displayed in Exhibit C.1 to Exhibit C.8. From all these investigations, it appears that most of the results are quite similar, whatever the category respondents belong too. This confirms that all the results presented in this survey are quite robust, if they are not related to a specific category of respondents.

1. Use of Alternative Equity Beta

The arguments for using alternative equity betas are the same for asset managers and institutional investors, for equity oriented countries and other countries, and whatever the size of assets under management (see Exhibit C.1), namely to gain exposure to relative risk factors and to improve diversification relative to cap-weighted index.

The main motivations for adopting alternative equity betas are the same for asset managers and institutional investors, for equity oriented countries and other countries, and whatever the size of assets under management (see Exhibit C.2), namely diversification and the potential for lower risk than cap-weighted indices.

62 - US, Canada, UK, Switzerland, Netherlands, Norway, Denmark, Sweden, Finland, Australia, New Zealand.

63 - France, Germany, Japan, Italy, Luxemburg, Belgium, Ireland, Spain, Croatia, Portugal, South Africa, Mauritius, Singapore, Hong Kong, Philippines, India, Brazil.

Exhibit C.1: Use of alternative equity beta by category of respondents. Please indicate your agreement with the following proposals on the usefulness of alternative equity beta strategies. The agreement was given on a scale from -2 (strong disagreement) to +2 (strong agreement). This exhibit indicates the average score obtained for each argument.

Alternative equity beta strategies are useful …	All respondents	Asset managers (82)	Institutional investors (26)	Equity oriented countries (77)	Other countries (50)	Size < 10bn (60)	Size >= 10bn (63)
… because they allow exposure to rewarded risk factors in a strategic equity allocation context	**1.22**	1.27	**1.16**	**1.28**	1.12	1.17	**1.31**
… because they improve diversification or index construction relative to cap-weighted index	1.13	**1.28**	0.85	1.07	**1.26**	**1.18**	1.08
.. because they reproduce the performance of active management through long only systematic factor investing	0.18	0.11	0.08	0.19	0.19	0.29	0.10
… because they replicate the performance of hedge funds through long/short factor investing	-0.26	-0.24	-0.4	-0.29	-0.22	-0.21	-0.30

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Exhibit C.2: Motivation for adopting alternative equity beta by category of respondents. What are the factors that have led you to adopt alternative equity beta strategies? The strength of the impact associated with each aspect was rated from 1 (weak motivation) to 5 (strong motivation). This exhibit gives the average score obtained for each argument.

	All respondents	Asset managers (82)	Institutional investors (26)	Equity oriented countries (77)	Other countries (50)	Size < 10bn (60)	Size >= 10bn (63)
Diversification	**3.78**	3.86	**3.63**	**3.86**	3.69	**3.84**	3.77
The potential for lower risk than CW indices	3.74	**3.86**	3.58	3.81	**3.71**	3.72	**3.85**
The potential for higher returns than CW indices	3.50	3.59	3.08	3.54	3.42	3.60	3.40
Reliable factor exposures of advanced beta indices	3.20	3.27	3.04	3.17	3.25	3.30	3.10
Transparency	3.07	3.30	2.58	3.00	3.21	3.26	2.92
Low cost	3.04	3.18	2.79	2.90	3.29	3.12	3.00

2. Familiarity with the Various Alternative Equity Beta

a. Long-only strategies

Among long-only strategies, Low Volatility, Equal-weighted and Value strategies have the highest familiarity for both asset managers and institutional investors, for both equity oriented countries and other countries, and whatever the size of assets under management, while decorrelation / diversification strategies have the lowest familiarity (see Exhibit C.3.a).

b. Long/short strategies

Among long/short strategies, results are more contrasted between asset managers and institutional investors, and depending of the size of assets under management, while the results are quite similar between equity oriented countries and other countries for the three strategies with the highest familiarity (see Exhibit C.3.b)

Exhibit C.3.a: Familiarity with long-only strategies by category of respondents. Which alternative equity beta strategies are you familiar with? This exhibit gives the average score obtained for each strategy. The average score was obtained by averaging the familiarity score of five criteria (construction principles, implementation, long-term outperformance, drivers of outperformance, underlying risks) rated from -2 (do not know about the topic) to +2 (very familiar).

Long Only strategies (Average score)	All respondents	Asset managers (82)	Institutional investors (26)	Equity oriented countries (77)	Other countries (50)	Size < 10bn (60)	Size >= 10bn (63)
Value	**1.16**	1.24	1.06	**1.27**	1.00	1.20	1.20
Low Volatility / Minimum Volatility	1.15	**1.29**	1.02	1.21	**1.06**	**1.21**	1.12
Equal weighted	1.15	1.26	**1.11**	1.23	1.02	1.08	**1.23**
Fundamental weighted	1.06	1.21	0.87	1.11	0.97	1.04	1.11
Momentum	0.93	1.06	0.68	0.94	0.90	0.85	1.02
Risk parity / Equal risk contribution	0.85	0.92	0.89	0.82	0.89	0.88	0.83
Decorrelation / diversification approaches	0.40	0.46	0.30	0.40	0.46	0.53	0.36

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Exhibit C.3.b: Familiarity with long / short strategies by category of respondents. Which alternative equity beta strategies are you familiar with? This exhibit gives the average score obtained for each strategy. The average score was obtained by averaging the familiarity score of five criteria (construction principles, implementation, long-term outperformance, drivers of outperformance, underlying risks) rated from -2 (do not know about the topic) to +2 (very familiar).

Long / Short strategies (Average score)	All respondents	Asset managers (82)	Institutional investors (26)	Equity oriented countries (77)	Other countries (50)	Size < 10bn (60)	Size >= 10bn (63)
Timing strategies that go long or short in aggregate market exposure (e.g. trend following strategies)	**0.54**	**0.61**	0.35	**0.52**	**0.58**	**0.55**	**0.57**
Single factor strategies that exploit value premium	0.46	0.48	0.41	0.48	0.41	0.34	0.57
Single factor strategies that exploit momentum	0.45	0.56	0.25	0.44	0.46	0.32	0.57
Single factor strategies that exploit another factor driving return differences across stocks	0.39	0.39	**1.20**	0.44	0.34	0.26	0.56
Passive hedge fund replication (portfolios of investable factors that mimic hedge fund index returns)	0.21	0.22	0.09	0.31	0.05	0.14	0.31
Systematic strategies based on corporate events (such as mergers)	0.19	0.26	0.04	0.25	0.10	0.15	0.26

3. Evaluation Process

Respondents allocate relatively few resources for evaluation of alternative equity beta strategies. It appears that there are no differences between asset managers and institutional investors or between countries. Differences are to be found depending on size of assets under management, with higher numbers of resources for higher sizes of assets under management (see Exhibit C.4).

The average rating of the challenges for evaluation of investment strategies and products is quite similar for evaluation of advanced beta offerings, whatever the category of respondents (see Exhibit C.5), while the perception of challenges for evaluation of active managers differs according to the amount of assets under management. It appears to be a greater challenge for companies with a lower amount of assets under management. Evaluation of cap-weighted indices and passive investment products is also a greater challenge for asset managers, countries that are less oriented to equities and companies with a lower amount of assets under management.

Exhibit C.4: Resources for evaluation process by category of respondents. Please indicate the average number of staff mainly concerned with each type of investment evaluation.

Average number of full time staff mainly concerned with:	All respondents	Asset managers (82)	Institutional investors (26)	Equity oriented countries (77)	Other countries (50)	Size < 10bn (60)	Size >= 10bn (63)
Evaluation of advanced beta offerings	1.77	1.80	1.67	1.76	1.79	1.47	2.12
Evaluation of cap-weighted indices and passive investment products	1.87	1.73	1.78	1.79	2.00	1.60	2.20
Evaluation of active managers	**3.42**	**3.43**	**3.56**	**3.35**	**3.53**	**2.53**	**4.49**

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Exhibit C.5: Challenges for evaluation of investment strategies by category of respondents. This table only displays the average rating of a list of challenges proposed to respondents (See Exhibit 3.4 for a detailed result for all respondents). Challenges were rated from 1 (weak challenge) to 5 (very strong challenge).

Average rating of challenges	All respondents	Asset managers (82)	Institutional investors (26)	Equity oriented countries (77)	Other countries (50)	Size < 10bn (60)	Size >= 10bn (63)
Evaluation of adavanced beta offerings	**3.21**	**3.18**	**3.17**	**3.15**	**3.28**	**3.20**	**3.18**
Evaluation of cap-weighted indices and passive investment products	2.02	1.97	1.67	1.87	2.27	2.24	1.85
Evaluation of active managers	2.87	2.81	2.70	2.89	2.90	3.18	2.59

4. Strategy Combinations

Respondents tend to agree that advanced beta has strong diversification potential through various strategies whatever the category they belong to (see Exhibit C.6).

5. Factors as Key Performance Drivers

Factors are seen as the main performance drivers of alternative equity beta strategies whatever the category of respondents (see Exhibit C.7).

Exhibit C.6: Views on combinations of alternative equity beta strategies by category of respondents. The respondents were asked to express their agreement with the following statements relating to the combination of alternative equity beta strategies on a scale from -2 (strongly disagree) to +2 (strongly agree).

Advanced beta has strong potential in this area	All respondents	Asset managers (82)	Institutional investors (26)	Equity oriented countries (77)	Other countries (50)	Size < 10bn (60)	Size >= 10bn (63)
Static combinations of alternative equity beta strategies to diversify across different types	0.84	0.92	0.88	0.94	0.70	0.96	0.74
Tactical switching across alternative equity beta strategies to exploit predictability in strategy returns	0.55	0.67	0.20	0.49	0.67	0.51	0.64
Tactical switching across CW and alternative equity beta to exploit predictability in strategy returns or tracking error	0.40	0.41	0.28	0.37	0.47	0.57	0.29

Exhibit C.7: Views on performance of alternative equity beta strategies by category of respondents. Please indicate your agreement / disagreement with the following statements regarding the performance of alternative equity beta strategies compared to cap-weighted indices on a range from -2 (totally disagree) to +2 (completely agree).

Agreement with statement	All respondents	Asset managers (82)	Institutional investors (26)	Equity oriented countries (77)	Other countries (50)	Size < 10bn (60)	Size >= 10bn (63)
The performance of alternative equity beta strategies is explained by factor tilts	1.04	1.07	1.04	1.07	0.98	0.89	1.17
The performance of alternative equity beta strategies is explained by rebalancing effects	0.39	0.32	0.50	0.41	0.39	0.44	0.36
The performance of alternative equity beta strategies is explained by the fact that they are less concentrated than cap-weighted indices	0.27	0.40	-0.04	0.19	0.44	0.50	0.11
The performance of alternative equity beta strategies is explained by the fact that they exploit the magic of diversification and take into account the correlation across stocks	0.21	0.25	0.13	0.09	0.45	0.32	0.16
The performance of alternative equity beta strategies is explained by data mining	-0.20	-0.30	-0.21	-0.36	0.07	-0.31	-0.07

Appendix

6. Likely Explanations of Importance of Factors

Factors premia are seen both as a compensation for risk and results of behavioural biases of investors whatever the category respondents belong to (see Exhibit C.8).

Exhibit C.8: Explanation for factor premia by category of respondents. Which do you think is the most likely explanation for the value, small-cap, momentum and low volatility premium documented in the academic literature? Please indicate how important/credible the following interpretation is on a scale from 0 (not at all credible) to 5 (highly credible)

Average results	All respondents	Asset managers (82)	Institutional investors (26)	Equity oriented countries (77)	Other countries (50)	Size < 10bn (60)	Size >= 10bn (63)
Explained as compensation for risk	2.93	2.99	2.66	2.78	2.84	2.93	2.95
Explained by behavioural biases of investors	3.55	3.60	3.34	3.49	3.49	3.35	3.74
Explained by many researchers examining the same data and identifying a pattern which is unlikely to persist in the future (data mining)	2.23	2.28	1.89	1.89	2.07	2.30	2.19

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About Société Générale Prime Services

About EDHEC-Risk Institute

About EDHEC-Risk Institute

Founded in 1906, EDHEC is one of the foremost international business schools. Accredited by the three main international academic organisations, EQUIS, AACSB, and Association of MBAs, EDHEC has for a number of years been pursuing a strategy of international excellence that led it to set up EDHEC-Risk Institute in 2001. This institute now boasts a team of over 95 permanent professors, engineers and support staff, as well as 48 research associates from the financial industry and affiliate professors..

The Choice of Asset Allocation and Risk Management

EDHEC-Risk structures all of its research work around asset allocation and risk management. This strategic choice is applied to all of the Institute's research programmes, whether they involve proposing new methods of strategic allocation, which integrate the alternative class; taking extreme risks into account in portfolio construction; studying the usefulness of derivatives in implementing asset-liability management approaches; or orienting the concept of dynamic "core-satellite" investment management in the framework of absolute return or target-date funds.

Academic Excellence and Industry Relevance

In an attempt to ensure that the research it carries out is truly applicable, EDHEC has implemented a dual validation system for the work of EDHEC-Risk. All research work must be part of a research programme, the relevance and goals of which have been validated from both an academic and a business viewpoint by the Institute's advisory board. This board is made up of internationally recognised researchers, the Institute's business partners, and representatives of major international institutional investors. Management of the research programmes respects a rigorous validation process, which guarantees the scientific quality and the operational usefulness of the programmes.

Six research programmes have been conducted by the centre to date:

- Asset allocation and alternative diversification
- Style and performance analysis
- Indices and benchmarking
- Operational risks and performance
- Asset allocation and derivative instruments
- ALM and asset management

These programmes receive the support of a large number of financial companies. The results of the research programmes are disseminated through the EDHEC-Risk locations in Singapore, which was established at the invitation of the Monetary Authority of Singapore (MAS); the City of London in the United Kingdom; Nice and Paris in France; and New York in the United States.

EDHEC-Risk has developed a close partnership with a small number of sponsors within the framework of research chairs or major research projects:

- Core-Satellite and ETF Investment, *in partnership with Amundi ETF*
- Regulation and Institutional Investment, *in partnership with AXA Investment Managers*
- Asset-Liability Management and Institutional Investment Management, *in partnership with BNP Paribas Investment Partners*
- Risk and Regulation in the European Fund Management Industry, *in partnership with CACEIS*
- Exploring the Commodity Futures Risk Premium: Implications for Asset Allocation and Regulation, *in partnership with CME Group*

About EDHEC-Risk Institute

• Asset-Liability Management in Private Wealth Management, *in partnership with Coutts & Co.*
• Asset-Liability Management Techniques for Sovereign Wealth Fund Management, *in partnership with Deutsche Bank*
• The Benefits of Volatility Derivatives in Equity Portfolio Management, *in partnership with Eurex*
• Structured Products and Derivative Instruments, *sponsored by the French Banking Federation (FBF)*
• Optimising Bond Portfolios, in partnership *with the French Central Bank (BDF Gestion)*
• Asset Allocation Solutions, *in partnership with Lyxor Asset Management*
• Infrastructure Equity Investment Management and Benchmarking, *in partnership with Meridiam and Campbell Lutyens*
• Investment and Governance Characteristics of Infrastructure Debt Investments, *in partnership with Natixis*
• Advanced Modelling for Alternative Investments, *in partnership with Newedge Prime Brokerage*
• Advanced Investment Solutions for Liability Hedging for Inflation Risk, *in partnership with Ontario Teachers' Pension Plan*
• The Case for Inflation-Linked Corporate Bonds: Issuers' and Investors' Perspectives, *in partnership with Rothschild & Cie*
• Solvency II, *in partnership with Russell Investments*
• Structured Equity Investment Strategies for Long-Term Asian Investors, *in partnership with Société Générale Corporate & Investment Banking*

The philosophy of the Institute is to validate its work by publication in international academic journals, as well as to make it available to the sector through its position papers, published studies, and conferences.

Each year, EDHEC-Risk organises three conferences for professionals in order to present the results of its research, one in London (EDHEC-Risk Days Europe), one in Singapore (EDHEC-Risk Days Asia), and one in New York (EDHEC-Risk Days North America) attracting more than 2,500 professional delegates.

EDHEC also provides professionals with access to its website, www.edhec-risk.com, which is entirely devoted to international asset management research. The website, which has more than 65,000 regular visitors, is aimed at professionals who wish to benefit from EDHEC's analysis and expertise in the area of applied portfolio management research. Its monthly newsletter is distributed to more than 1.5 million readers.

EDHEC-Risk Institute: Key Figures, 2013-2014

Nbr of permanent staff	97
Nbr of research associates	26
Nbr of affiliate professors	28
Overall budget	€13,500,000
External financing	€10,100,000
Nbr of conference delegates	1,782
Nbr of participants at EDHEC-Risk Institute Executive Education seminars	1,576

About EDHEC-Risk Institute

The EDHEC-Risk Institute PhD in Finance

The EDHEC-Risk Institute PhD in Finance is designed for professionals who aspire to higher intellectual levels and aim to redefine the investment banking and asset management industries. It is offered in two tracks: a residential track for high-potential graduate students, who hold part-time positions at EDHEC, and an executive track for practitioners who keep their full-time jobs. Drawing its faculty from the world's best universities, such as Princeton, Wharton, Oxford, Chicago and CalTech, and enjoying the support of the research centre with the greatest impact on the financial industry, the EDHEC-Risk Institute PhD in Finance creates an extraordinary platform for professional development and industry innovation.

Research for Business

The Institute's activities have also given rise to executive education and research service offshoots. EDHEC-Risk's executive education programmes help investment professionals to upgrade their skills with advanced risk and asset management training across traditional and alternative classes. In partnership with CFA Institute, it has developed advanced seminars based on its research which are available to CFA charterholders and have been taking place since 2008 in New York, Singapore and London.

In 2012, EDHEC-Risk Institute signed two strategic partnership agreements with the Operations Research and Financial Engineering department of Princeton University to set up a joint research programme in the area of risk and investment management, and with Yale School of Management to set up joint certified executive training courses in North America and Europe in the area of investment management.

As part of its policy of transferring know-how to the industry, EDHEC-Risk Institute has also set up ERI Scientific Beta. ERI Scientific Beta is an original initiative which aims to favour the adoption of the latest advances in smart beta design and implementation by the whole investment industry. Its academic origin provides the foundation for its strategy: offer, in the best economic conditions possible, the smart beta solutions that are most proven scientifically with full transparency in both the methods and the associated risks.

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EDHEC-Risk Institute Publications (2012-2015)

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• Deguest, R., L. Martellini, and A. Meucci. Risk parity and beyond - From asset allocation to risk allocation decisions (June).

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- Uppal, R. Financial Regulation (April).
- Amenc, N., F. Ducoulombier, F. Goltz, and L. Tang. What are the risks of European ETFs? (January).

Notes

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