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Scientific Beta
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Scientific Beta Multi-Strategy Factor Indices: Combining Factor Tilts and Improved Diversification

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Abstract

This paper argues that current smart beta investment approaches only provide a partial answer to the main shortcomings of cap-weighted indices, and introduces Scientific Beta Multi-Strategy Factor Indices which are constructed using a new approach to equity investing referred to as smart factor investing. It then provides an assessment of the benefits of addressing the two main problems of cap-weighted indices (their undesirable factor exposures and their heavy concentration) simultaneously by constructing factor indices that explicitly seek exposures to rewarded risk factors, while diversifying away unrewarded risks. The results suggest that ERI Scientific Beta Multi-Strategy Factor Indices lead to considerable improvements in risk-adjusted performance. For long-term US data, smart factor indices for a range of different factor tilts consistently outperform cap-weighted factor tilted indices, and factor indices from popular commercial index providers. Compared to the broad cap-weighted index, smart factor indices roughly double the risk-adjusted return (Sharpe ratio). Outperformance of such indices persists at levels ranging from 2.92% to 4.46% annually, even when assuming unrealistically high transaction costs. Moreover, by providing explicit tilts to consensual factors, such indices improve upon many current smart beta offerings where, more often than not, factor tilts result as unintended consequences of ad hoc methodologies.

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1. Addressing the Problems of Cap-Weighted Indices

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Alternative equity indices or smart beta strategies are seen to provide tremendous growth potential. A recent survey (the EDHEC European ETF Survey 2013 by Ducoulombier *et al.*, 2014) reveals that while only 30% of investment professionals already use products tracking smart beta indices, more than one third of respondents are considering investing in such products in the near future.[1] Current smart beta investment approaches only provide a partial answer to the main shortcomings of cap-weighted indices. Therefore, ERI Scientific Beta has developed a new approach to equity investing referred to as smart factor investing, which uses consensual results from asset pricing theory concerning both the existence of factor premia and the importance of diversification, to go beyond existing smart beta approaches which provide partial solutions by only addressing one of these issues. Using the USA Long Term Track Records (40 years) of Scientific Beta Multi-Strategy Factor Indices, the paper provides an assessment of the benefits of addressing the two main problems of cap-weighted indices (their undesirable factor exposures and their heavy concentration) simultaneously by constructing factor indices that explicitly seek exposures to rewarded risk factors, while diversifying away unrewarded risks.

Asset pricing theory in fact suggests that there are two main challenges involved in a sound approach to equity investing. The first challenge is the efficient diversification of unrewarded risks, where "diversification" means "reduction" or "cancellation" (as in "diversify away"). Indeed, unrewarded risks are by definition not attractive for investors who are inherently risk-averse and therefore only willing to take risks if there is an associated reward to be expected in exchange for such risk taking, as shown by Harry Markowitz in his seminal work on portfolio diversification (Markowitz, 1952).[2] The second challenge is the efficient diversification of rewarded risks. Here the goal is not to diversify away rewarded risk exposures so as to eventually eliminate or at least minimise them, since this would imply giving up on the risk premia; the goal is instead to efficiently allocate to rewarded risk factors so as to achieve the highest reward per unit of risk. In William Sharpe's (1964) CAPM, there is a single rewarded risk factor so the second challenge is non-existent, and the only focus should be on holding a well-diversified proxy for the market portfolio. In a multi-factor world, where the equity risk premium is multi-dimensional (including not only market risk, but also size, B/M, momentum, volatility, etc.), an important component of an investor's equity investment process is the determination of the appropriate (e.g. Sharpe ratio maximising) allocation to these rewarded risk exposures.

This analysis of the dual challenges to rational equity investing is enlightening with respect to a proper understanding of the intrinsic shortcomings of cap-weighted (CW) indices that are typically used as default investment benchmarks by asset owners and asset managers. On the one hand, CW indices are ill-suited investment benchmarks because they tend to be concentrated portfolios that contain an excessive amount of unrewarded risk. On the other hand, CW indices implicitly embed a bundle of factor exposures that are highly unlikely to be optimal for any investor, if only because they have not been explicitly controlled for. For example, CW indices show (by construction) a large

1 - Estimates of the total assets managed in smart beta funds or mandates are notoriously hard to get with sufficient reliability as data on dedicated mandates which likely play a considerable role for smart beta adoption by sophisticated institutional clients is not available publicly, and identification of the smart beta category is difficult. However, some observers put the total assets at $200 bn as of 2013. 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). CNBC (Smart beta: Beating the market with an index fund", CNBC, November 7th, 2013, <http://www.cnbc.com/id/101149598>) reported that about seven percent of ETF assets are linked to smart beta indices and such ETFs have seen a 43 percent growth over 2013 compared to 16 percent growth of the overall ETF market. Investment consultancy firm Towers Watson has stated that its institutional clients have allocated about USD 20 bn to smart beta strategies at the end of 2012, an increase of 33% over levels seen one year earlier (See <http://www.next-finance.net/Smart-Beta-strategies-continue-to>).

2 - Unrewarded risks can be risks specific to a particular company or systematic risk exposure for which no reward is expected. It can be shown that for a factor model with the assumption of zero alpha and replicable factors, the specific risk of the true (long-short) MSR portfolio is zero.

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cap bias and a growth bias, while the academic literature has instead shown that small cap and value where the positively rewarded risk exposures.

This analysis also allows light to be shed on the benefits and shortcomings of existing alternatives to CW indices. Broadly speaking, there have been two main innovations in the recent years. On the one hand, a number of index providers have launched so-called smart indices or smart beta indices, which focus on addressing the first shortcoming of CW indices, namely their excessive concentration that leads to an excessive presence of unrewarded risk. These first generation smart beta indices (Smart Beta 1.0) include various approaches that are based either on scientific diversification (e.g. indices aiming at implementing a minimum variance or max Sharpe ratio allocation to selected stocks subject to a number of constraints either on weights or on parameter estimates that are meant to improve the robustness of the portfolio construction methodology) or naive diversification (equal-dollar contribution or equal risk contribution indices).[3] One problem with these smart beta indices, however, is that they fail to address the second problem, namely the explicit control of rewarded risk exposures. Hence, by switching from a CW index to an EW or GMV index for example, the investor is switching from one arbitrary bundle of factor exposures to another arbitrary bundle of factor exposures, which may or may not be consistent with the investor's needs and beliefs.

On the other hand, index providers have also launched so called factor indices, which focus on addressing the second shortcoming of CW indices, namely their lack of controlled factor exposure.[4] Such factor indices are meant to be investable long-only or long-short proxies for some of the rewarded factors that have been analysed in academic literature, such as the value factor, the size factor, the momentum factor or the low vol factor.[5] One problem with these factor indices, however, is that they fail to address the first problem, namely the excessive concentration problem leading to the presence of unrewarded risk. This is because the weighting scheme used in the design of factor indices is either CW (leading to an excessive degree of concentration) or factor exposure maximising (also leading to a lack of diversification). In a nutshell, CW indices suffer from two main problems, namely the presence of excessive concentration and the presence of an underlying arbitrary set of factor exposures. The existing Smart Beta 1.0 generation alternatives (namely smart indices or factor indices) are reasonably successful attempts at addressing one of these problems, but being a pre-packaged bundle of factor exposures and weighting scheme methodologies, they leave the other dimension unattended.

In the end, risk factors are like vectors; they are defined by the direction they point to, but also by their size. Having access to a good proxy for a factor is hardly relevant if the investable proxy only gives access to a fraction of the fair reward per unit of risk to be expected from the factor exposure because of the presence of unrewarded risk due to excessive concentration. ERI Scientific Beta proposes a solution to these two problems in the form of Multi-Strategy Factor Indices, which are smart (meaning well-diversified) indices with selected factor exposures that naturally combine the benefits of smart indices and the benefits of factor indices. In brief, smart factor indices are meant to be the outcome of a process carefully distinguishing the security selection stage from the portfolio

3 - In fact, scientific and naive approaches to diversification are not competing approaches; in particular, introducing some form of shrinkage of the scientifically diversified portfolio towards a naively diversified (equal-weight or equal risk parity) portfolio has been shown to improve the out-of-sample risk-adjusted performance.

4 - Fundamental indices and other indices that weight stocks according to some fundamental measure of economic size (Arnott *et al.*, 2005) do not explicitly try and improve the concentration problem nor do they explicitly aim at addressing the problem of inefficient factor exposure. This is the reason why we do not include these indices in the aforementioned list of recent innovations. Such approaches can be regarded as ad hoc attempts at constructing an index based on a measure of company size that is different from market cap.

5 - The low vol factor is in fact an anomaly, since it stipulates that the most risky stocks underperform, as opposed to outperform, the least risky stocks (Ang *et al.*, 2006; Baker, Bradley, and Wurgler, 2011; Bali, Cakici, and Whitelaw, 2011).

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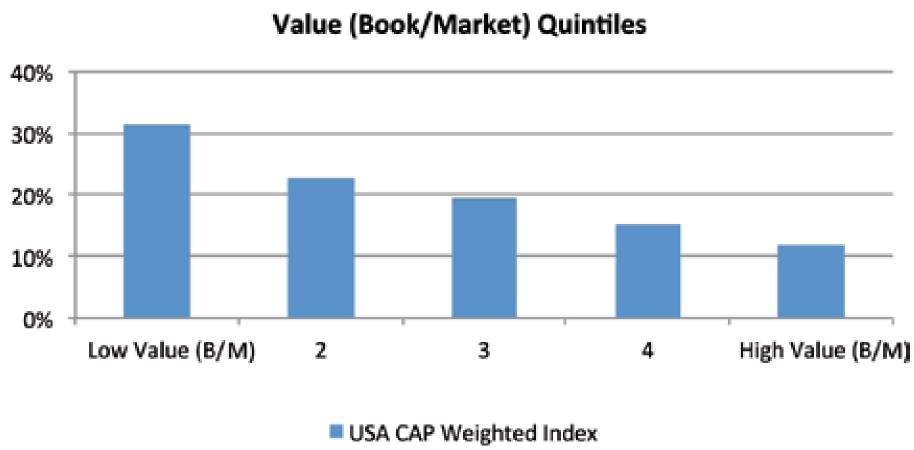
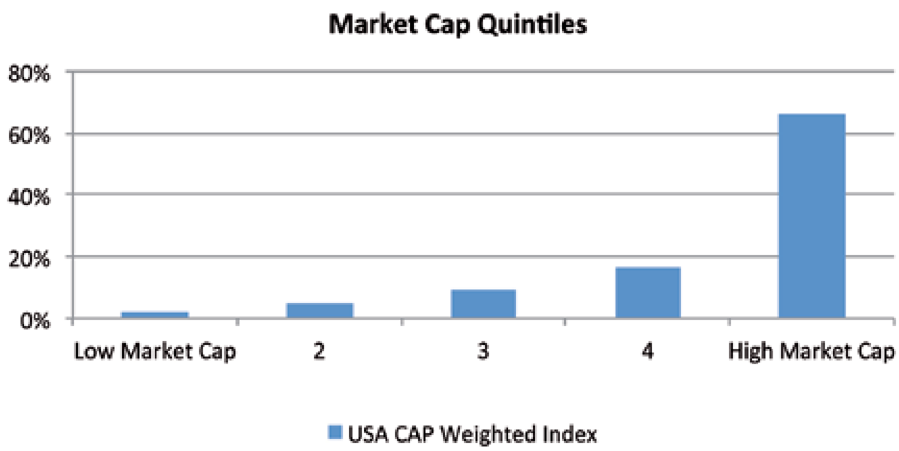
construction process.[6] The security selection stage is meant to ensure that the right factor-tilt will be associated to each index. For example, one would select a set of value stocks to construct a proxy for a value factor or a set of low volatility stocks to construct a proxy for the low volatility factor. On the other hand, the portfolio construction phase is meant to seek to diversify away unrewarded risk as much as possible by using some naive or scientific approach to diversification. As such, the factor index is made "smart" (meaning better diversified), and the investor can hope to gain a larger fraction of the reward (Sharpe ratio) associated with these factors.

Exhibit 1: Drawbacks of CW Indices – USA CW Index is based on the 500 largest US stocks by market capitalisation. Book-to-Market quintiles and market Cap quintiles are formed every quarter and average values across 160 quarters in the period from 31/12/1972 to 31/12/2012 are reported.





The white paper also introduces a formal framework that can be used by investors to allocate to the various Multi-Strategy Factor Indices, once they have been carefully constructed. This portfolio construction process distinguishes itself from the unconditional approach, where the investor seeks the optimal exposure to risk factors that are rewarded in the long-term by utilising a sophisticated

6 - This careful distinction lies at the heart of Smart Beta 2.0 approach (Amenc and Goltz, 2013).

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risk allocation framework. A sound approach to smart factor index allocation requires the proper execution of three different steps:
• Choice of factors that are rewarded in the long term;
• Designing factor tilted portfolios that capture the fair risk-adjusted reward associated with exposure to the factor;
• Choice of a methodology for deriving the optimal multi-factor exposures.

In Section 2, we describe the selection of appropriate factors. In Section 3, we describe the design of well-diversified factor indices and compare them with the conventional approach to factor indices. Section 4 presents a set of robustness checks (implementation issues and conditional performance) and an outlook on the use of smart factor indices in multi-factor allocations. The last section provides conclusions.

1. Addressing the Problems of Cap-Weighted Indices

2. Identification of a Suitable Set of Factors

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In this section, we review the empirical asset pricing literature to identify the factors that are most likely to bear a long-term reward. Both equilibrium models such as Merton's (1973) inter-temporal capital asset pricing model and no 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 when marginal utility is high (Cochrane, 2001). 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.

The first order necessary condition for a factor to be deemed important is the existence of an empirical research which shows that the identified factor has a significant impact on the cross section of stock returns in US and international equity markets. Several systematically rewarded risk factors have been documented in literature; Harvey *et al.*, 2013) document a total of 314 of such factors. The practice of identifying empirical factors is referred to as '*factor fishing*'. Therefore, 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.[7]

Fama and French have identified that value (book-to-market) and size (market cap) explain average asset returns, as a complement to the market beta (Fama and French, 1993). Carhart (1997) empirically proved the existence of another priced factor – the momentum factor. Another risk factor in the cross section of stock returns is liquidity. In fact, it has been argued that investors want to be compensated for taking on liquidity risk, as investors are naturally averse to assets with evaporating liquidity in times of market stress (see Nagel 2012). An additional characteristic that allows portfolios with particular risk factor exposure to be generated is a stock's dividend yield (see Boudoukh *et al.*, 2007 for a discussion of the cross sectional link between stock dividend yield and returns). The low volatility factor, which qualifies as an anomaly rather than a risk factor, is the result of the famous 'volatility puzzle,' which states that low-volatility stocks tend to outperform high-volatility stocks in the long run (Ang *et al.*, 2006). For these widely documented factors, ERI Scientific Beta produces dedicated factor indices, that provide tilts for six factors, as shown on the following page.

In addition to the factor tilts associated with long term rewards, Scientific Beta offers the opposite tilts, thus allowing for the implementation of tactical allocation strategies where investors could witch for example between high Momentum and low momentum exposure, value and growth exposure etc.

7 - It should be noted that not all investors are necessarily interested in harvesting every available risk premium. In fact some investors prefer to pay the premium to avoid exposure to a certain risk factor (e.g. in the case of the illiquidity premium). However, some investors could decide to try to capture the reward associated with a risk premium, even if this reward is related to taking on additional risk. For example, while the reward may occur in equilibrium due to a factor paying off poorly in bad times (when marginal utility of consumption is high), investors who have a particularly long time horizon maybe less sensible to such risks. Long horizon investors may thus be particularly inclined to seek exposure to such rewarded factors, from which short term investors may shy away due to the associated risk

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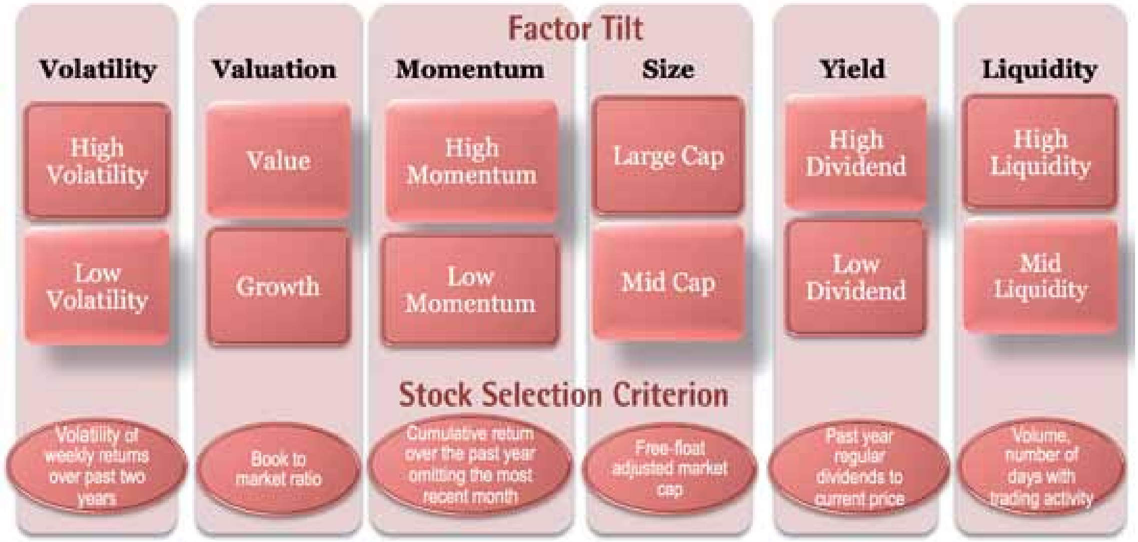

It should be noted that ERI Scientific Beta has made a parsimonious choice by only including a limited number of factors. One can create a much broader set of factors at the cost of relying on factors which are less well documented. For example, recently, an evolving literature and industry practices propose to consider a "Quality" factor. This factor could be based on a simple company attribute like gross profitability (Novy-Marx, 2013) or more complex composite measures like a combination of profitability, growth, safety, and dividend payout (Asness *et al.*, 2013a). We have made the choice to not include this factor as empirical evidence is much more recent and the definition less consensual than for the factors listed above.

Moreover, among all possible tilts on six factors for which ERI Scientific Beta provides indices, we have selected four main factor tilts for detailed discussion in this paper. Below, we concentrated on the low size, value, momentum and low volatility tilts. However, the conceptual arguments we make in this paper carry through to any rewarded risk factors.

2.1 Empirical Illustration

In this section, we provide empirical evidence of risk premia for four well known equity risk factors – size, value, momentum and low volatility. Exhibit 2 shows the returns of signal weighted quintile portfolios that represent portfolios with varying degree of exposure to each factor. Signal weighting is done by weighting the stocks in proportion to their rank by relevant sorting characteristic following Asness *et al.*, 2013b). For example, in any value quintile consisting of 100 stocks, the stock with highest B/M ratio will have 100 times more weight than the stock with lowest B/M ratio. Same rank based weighting is followed in all quintiles for all factors. The difference between Value and Growth quintiles is 11.62% and that between Mid Cap and Large Cap quintiles is 4.97%.

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Exhibit 2: Performance of quintile portfolios sorted by factors and weighted by rank – The exhibit shows mean annualized returns of quintile portfolios. For each factor, the quintiles are constructed on related stock characteristics – market cap for size, B/M ratio for value, past 1 year minus 1month returns for momentum, and past 2-year volatility for low volatility. Stocks in each quintile are rank weighted. All portfolios are rebalanced quarterly and the analysis is based on daily total returns from 31/12/1972 to 31/12/2012 (40 years).

	Market Cap	B/M Ratio	Momentum	Volatility
High	9.74%	19.67%	15.19%	10.21%
Quintile 2	10.92%	13.78%	13.43%	12.31%
Quintile 3	13.23%	12.07%	14.01%	12.17%
Quintile 4	12.14%	9.99%	11.99%	12.97%
Low	14.71%	8.05%	9.64%	12.44%
High-Low	-4.97%	11.62%	5.56%	-2.23%

The debate about the existence of positive premia for these factors is far from closed. While positive premia for these factors are documented in an extensive literature, some authors question the robustness or the persistence of the reward associated with these factors. As an example, one may consider the ongoing debate on the low risk premium. Early empirical evidence suggests that the relation between systematic risk (stock beta) and return is flatter than predicted by the CAPM (Black, Jensen, and Scholes, 1972). More recently, Ang, Hodrick, Xing, and Zhang (2006, 2009) find that stocks with high idiosyncratic volatility have had low returns. Other papers have documented a flat or negative relation between total volatility and expected return. However, a number of recent papers have questioned the robustness of such results and show that the findings are not robust to changes to portfolio formation (Bali and Cakici, 2008) or to adjusting for short-term return reversals (Huang *et al.*, 2010). More generally, McLean and Pontiff (2013) assess empirically if risk premia for a range of factor have remained significant after the effect has been widely publicised.

In fact, one can argue that empirical evidence will not be sufficient to draw a clear conclusion as to which set of factors are acceptable for a given investors. Empirical results always carry a risk 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; see Harvey *et al.*, 2013). Therefore, the choice of relevant factors should consider the economic rationale behind the reward for a given factor (see Kogan and Tian, 2013). The following subsection explains why investors should expect a reward for the four main risk factors discussed in this paper. Moreover, simple, straightforward factor definitions may be useful to avoid the risk of data-mining of complex and unproven factor definitions.[8]

2.2 Economic Rationale

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 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,

8 - It has been argued that value-tilted indices, which draw on proprietary and ad hoc definitions of composite scores, such as commercially available fundamentally weighted indices, are highly sensitive to the methodological choices made in the index construction process (see e.g. Blitz and Swinkels, 2008). Amenc (2011) shows that fundamental indices which differ in methodology such as different choices for fundamental variable selection, turnover control and rebalancing, could result in very different short term performance; as much as 10% difference in returns in a given year.

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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 over-reaction 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. In fact, even if the average investor makes systematic errors due to behavioural "biases", it could still be possible that some rational investors who are not subject to such biases exploit any small opportunity resulting from the irrationality of the average investor. The trading activity of such smart investors may then make the return opportunities disappear. Therefore, behavioural explanations of persistent factor premia often introduce so called "limits to arbitrage", which prevent smart investors from fully exploiting the opportunities arising from the irrational behaviour of other investors. The most commonly-mentioned limits to arbitrage are short-sales constraints and funding-liquidity constraints. The table below summarises the main economic explanations for common factor premia.

	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.	N.A.

Value

Zhang (2005) provides a rationale for the value premium based on costly reversibility of investments. The stock price of value firms is mainly made up of tangible assets which are hard to reduce while growth firms' stock price is mainly driven by growth options. Therefore value firms are much more affected by bad times. Choi (2013) shows that value firms have increasing betas in down markets (due to rising asset betas and rising leverage) while growth firms have more stable betas. The value premium can thus be interpreted as compensation for the risk of suffering from losses in bad times. In an influential paper, Lakonishok, Shleifer and Vishny (1994) argue that "value strategies exploit the suboptimal behaviour of the typical investor". Their explanation of the value premium focuses on the psychological tendency of investors to extrapolate recent developments into the future and to ignore evidence that is contrary to the extrapolation. Glamour firms with high recent growth thus tend to obtain valuations that correspond to overly optimistic forecasts while distressed firms obtain stock market valuations which are overly pessimistic.

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Momentum

Momentum stocks are exposed to macroeconomic risk. In particular, Liu and Zhang (2008) provide empirical evidence that past winners have temporarily higher loadings on the growth rate of industrial production. This higher sensitivity of firms with higher expected growth rates is a natural result of firm valuation and is similar to the higher interest rate sensitivity (duration) of bonds at high levels of interest rate (see Johnson, 2002). Low momentum stocks on the other hand have low expected growth and are less sensitive to changes in expected growth.

Behavioural explanations for momentum profits focus on the short-term over-reaction of investors. Daniel *et al.* (1998) show that two cognitive biases, overconfidence and self-attribution, can generate momentum effects. In particular, they show that investors will attribute the recent performance of the winning stocks they have selected to their stock picking skill and thus further bid up the prices for these stocks, thus generating a momentum effect in the short term, with stock prices only reverting to their fundamental values at longer horizons.

Low Risk

Frazzini and Pedersen (2014) provide a model in which liquidity-constrained investors are able to invest in leveraged positions of low-beta assets but are forced to liquidate these assets in bad times when their liquidity constraints mean they can no longer sustain the leverage. Thus low-risk assets are exposed to a risk of liquidity shocks and investors are compensated for this risk when holding low-beta assets. High-beta assets, on the other hand, expose investors to less liquidity risk and rational investors may thus require less expected return from these stocks than what would be in line with their higher market beta.

Behavioural explanations for the low-risk premium argue that high-risk stocks tend to have low returns because irrational investors bid up prices beyond their rational value. For example, Hong and Sraer (2012) show that when there is disagreement among investors on the future cash flow of firms, short sales constraints will lead to overpricing of stocks where investor disagreement is high. As disagreement increases with a stock’s beta, high-beta stocks are more likely to be overpriced.

Size

Small stocks tend to have lower profitability (in terms of return on equity) and greater uncertainty of earnings (see Fama and French, 1995), even when adjusting for book-to-market effects. Therefore, such stocks are more sensitive to economic shocks, such as recessions. It has also been argued that stocks of small firms are less liquid and expected returns of smaller firms have to be large in order to compensate for their low liquidity (Amihud and Mendelson, 1986). It has also been argued that smaller stocks have higher downside risk (Chan, Chen and Hsieh, 1985).

3. Scientific Beta Multi-Strategy Factor Indices: Turning Risk into a Choice rather than a Fate

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3.1 Conventional Approach to Factor Indices

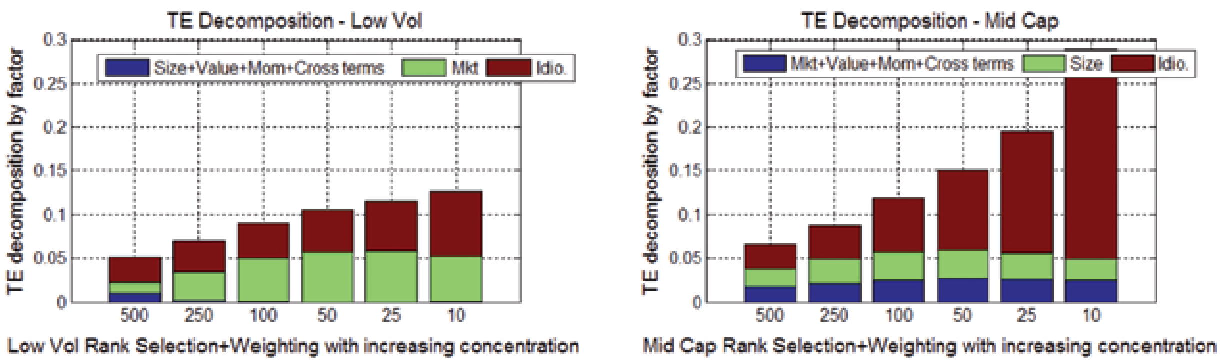
Conventional Factor indices fall into two major categories. The first involves selecting stocks that are most exposed to the desired risk factor and the application of a cap-weighting scheme to this selection. While this approach responds to one limitation of cap-weighted indices, namely the choice of 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.

Given that stocks are selected based on factor exposures, such an approach may lead to even higher levels of concentration than with broad CW indices, and thus to taking on unrewarded (firm specific) risks (too concentrated opportunity set might lead to high stock specific risks). To evaluate the effect of concentration on idiosyncratic risks, we construct rank weighted portfolios where we select N stocks from broad 500 universe based on a characteristics score (e.g. value) and then weight these stocks by same parameter (value) rank. N is set to be 500 and then decreased to lower levels till 10 stocks are reached. We then break down Tracking Error into contributions from different risk factors. We use Carhart four factors to perform this decomposition.

$$TE^2 = \sigma_\varepsilon^2 + \sum_F \beta^{F^2} Var(R_F) + 2 \sum_{F_i \neq F_j} \beta^{F_i}\beta^{F_j} Cov\left(R_{F_i}, R_{F_j}\right)$$

The results are shown in Exhibit 3. It is quite clear that when we reduce the number of stocks, the idiosyncratic risk of individual stocks comes into play and overall contributes to higher specific risk of the strategy. This remains true for all four factor tilts analysed.

Exhibit 3: Drawbacks of Highly Concentrated Factor Indices - The table shows the decomposition of relative risks of rank weighted portfolios with different levels of stock selection (increasing concentration) where the both selection and ranking variable is respectively Volatility/Cap/Book-to-Market/Momentum score. All statistics are annualised and daily total returns from 31-December-1972 to 31-December-2012 are used for the analysis. Cap-weighted index based on all stocks (without any kind of stock filtering) is used as the benchmark for relative risk and returns statistics.



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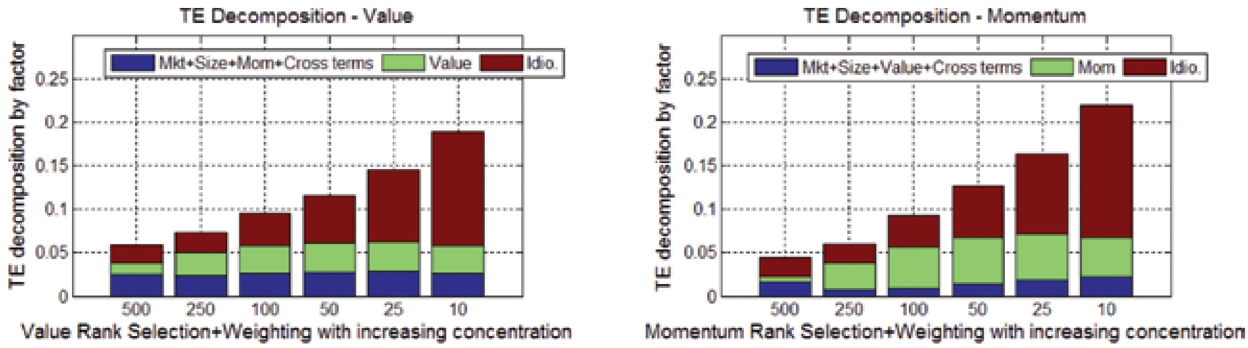

To overcome these difficulties, index providers that generally offer factor indices on the basis of the first two approaches have recently sought to take advantage of the development of smart beta indices to offer investors a new framework for factor investing (Bender *et al.*, 2013). In fact, index 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 tilts 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 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 which are not based on explicit factor choice, and which we refer to as Smart Beta 1.0, are not satisfactory both in terms of control of rewarded risk and in terms of diversification of the unrewarded risks.

3.2 Smart Beta 2.0 Approach to ERI Scientific Beta Multi-Strategy Factor Indices

An important challenge in factor index construction is to design well-diversified factor indices that capture rewarded risks while avoiding unrewarded risks. The Smart Beta 2.0 approach allows 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 and Goltz, 2013).

3. Scientific Beta Multi-Strategy Factor Indices: Turning Risk into a Choice rather than a Fate

Stock selection, the first step in Smart Beta 2.0, 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 the stock's 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 portfolio individual components. ERI Scientific Beta provides straightforward factor definitions, puts investors in control of their risks, and avoids the risk of data-mining of complex and unproven factor definitions. Stock universe is divided into 2 halves based on stock level characteristic and the half-universe thus obtained is used as the base for constructing multi-strategy factor indices. The table below shows the scoring rules used for universe split for the four main factor tilts. Scoring is done yearly at on the 1st Friday of Q2 using buffer rules with the exception of Momentum score which is done semi-annually.

Risk Factor	Scoring Criteria
Value	Ratio of available book value of shareholders' equity to company market cap
Momentum	Return over past 52 weeks, minus the last 4 weeks
Volatility	Standard deviation of weekly stock returns over the past 104 weeks
Size	Free float market cap

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 certain extent. For example, robustness of 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 a potential to be diversified away (Kan and Zhou, 2007; Amenc *et al.*, 2012). A Diversified Multi-Strategy approach,[9] which combines the 5 different weighting schemes in equal proportions, enables the non-rewarded risks associated with each of the weighting schemes to be diversified away.

Scientific Beta Multi-Strategy factor indices are constructed by applying Diversified Multi-Strategy weighting scheme on each stock selection. The Smart Beta 2.0 framework 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. ERI Scientific Beta allows investors to benefit from additional factors with reduced specific risks, which is something that simple cap-weighting does not permit. These indices are available for nine geographical universes: USA, UK, Eurozone, Europe ex UK, Japan, Asia Pacific ex Japan, Developed, Developed ex US, and Developed ex UK.

9 - 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.

3. Scientific Beta Multi-Strategy Factor Indices: Turning Risk into a Choice rather than a Fate

We now turn to an empirical analysis on US long term data of a set of Multi-Strategy factor indices constructed for the four main factors introduced above. All indices are rebalanced quarterly and dividends are reinvested in the index. The analytics on US indices in subsequent sections use 40 years daily total returns. We first assess the achievement of the desired factor tilts and then assess risk-adjusted performance. For the illustrations, we use Multi-Strategy Factor Indices on four rewarded factors that have been discussed earlier. They are – mid cap, high momentum, low volatility, and value.[10]

3.3 Obtaining Exposure to Desired Rewarded Risk Factors

First we examine how well these Multi-Strategy factor indices fulfil their first objective (i.e. to provide exposure to the desired risk factor). Exhibit 4 shows the Carhart 4-factor regression statistics for the Multi-Strategy factor indices and of cap-weighted (poorly diversified) factor indices. Mid Cap Multi-Strategy index has a size beta of 0.32, high Momentum Multi-Strategy index has a momentum beta of 0.17, and value tilted index has a value beta of 0.31. Similarly, low volatility smart factor index has low market beta (0.78), as low market beta stocks are usually also low volatility stocks. Cap weighted indices, by construction, load heavily on few large cap stocks. Therefore any alternative to cap weighting, especially diversification-based weighting schemes which aim to be more deconcentrated, will induce the exposure to small cap factor. As a result, smart factor indices have small size exposure as well however it is important to note that the magnitude of small size beta is largest for the smart factor index that is explicitly exposed to small size, (i.e. the Mid Cap Diversified Multi-Strategy index (0.32)), while the average small size beta for other three smart factor indices is 0.12. Similarly Momentum Diversified Multi-Strategy index has a momentum beta of 0.17 compared to the 0.01 average of others; and Value Diversified Multi-Strategy index has a value beta of 0.31 compared the 0.13 average of others.

The exercise shows that the simple stock selection process (prior optimisation) results in portfolios which have desired exposure ex-post. If one wants to have a strong factor tilt, using stock selection is the most transparent and simple to implement way to achieve it. In other words, a careful distinction between security selection and weighting scheme allows investors to turn risk into "a choice rather than a fate", to paraphrase an insightful comment by late Peter Bernstein (1996: Against the Gods: The Remarkable Story of Risk).

10 - On the ERI Scientific Beta platform, there exist 12 factors on which one can build smart factor indices. Six of them are known to be rewarded in long term (Mid Cap, Mid Liquidity, High Momentum, Low Volatility, Value, and High Dividend Yield) and other six are complementary to the rewarded side (Large Cap, High Liquidity, Low Momentum, High Volatility, Growth, and Low Dividend Yield).

3. Scientific Beta Multi-Strategy Factor Indices: Turning Risk into a Choice rather than a Fate

Exhibit 4: Exposure of USA Cap Weighted Factor Indices and USA MultiStrategy Factor Indices based on Scientific Beta Long Term Track Records to Equity Risk Factors – The exhibit shows 4-factor regression analysis indicators for Cap Weighted Factor Indices and MultiStrategy Factor Indices for four factor tilts – mid cap, high momentum, low volatility, and value. 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 largest 30% of stocks. Value factor is long the CW portfolio of highest 30% and short the CW portfolio of lowest 30% of B/M ratio stocks. Momentum factor is long the CW portfolio of highest 30% and short the CW portfolio of lowest 30% of 52-week (minus most recent 4 weeks) past return stocks. The regression coefficients (betas and alphas) statistically significant at 95% 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. All statistics are annualised. The analysis is based on daily total returns from 31/12/1972 to 31/12/2012 (40 years).

	Mid Cap		High Momentum		Low Volatility		Value	
	CW	Diversified Multi Strategy	CW	Diversified Multi Strategy	CW	Diversified Multi Strategy	CW	Diversified Multi Strategy
Ann Alpha	0.88%	**2.59%**	0.07%	**1.73%**	0.92%	**2.52%**	-0.58%	**2.26%**
Market Beta	**1.01**	**0.93**	**1.01**	**0.94**	**0.86**	**0.78**	**0.99**	**0.91**
Small Size Beta	**0.31**	**0.32**	**0.01**	**0.16**	**-0.14**	**0.02**	0.00	**0.16**
Value Beta	**0.15**	**0.16**	0.00	**0.09**	**0.05**	**0.14**	**0.42**	**0.31**
Momentum Beta	**0.02**	**0.00**	**0.20**	**0.17**	**-0.01**	0.00	**0.05**	**0.03**
R-squared	94.3%	92.0%	98.6%	95.5%	94.7%	90.2%	98.3%	95.0%

3.4 Avoiding Non-Rewarded Risk: Creating Well-Diversified Single Beta Indices

Exhibit 5 presents absolute performance summary of the four Multi-Strategy factor indices compared to those of Cap Weighted factor indices. As broad cap-weighted index remains the widely accepted reference, we use the broad cap weighted index based on 500 largest stocks as the benchmark. All factor tilted portfolios, irrespective of the weighting scheme used, outperform the broad cap-weighted index. It verifies that the four chosen risk factors do earn, an average, a positive risk premium in the long run.

For each factor tilt, the Multi-Strategy factor index earns higher returns than the CW factor index for the same tilt. Value and mid cap have been the most rewarding factors in the last 40 years in the US market. Mid Cap and Value smart factor indices earn a premium of 4.45% and 4.70% annual respectively. Low Volatility and High Momentum are comparatively less rewarded; however their smart factor indices have earned 2.90% and 3.56% excess returns respectively. If one looks at the risk-adjusted performance, Multi-Strategy factor indices consistently post superior Sharpe ratio than CW factor indices. Historical Daily 5% Value-at-Risk and Maximum Drawdown of Multi-Strategy factor indices and CW factor indices are similar. It shows that the increase in performance and the reduction in portfolio risk do not come at the cost of extreme risk.

Both Multi-Strategy and Cap Weighted factor indices are exposed to systematic risk factors which are quite different from those of broad CW index. Reward to these risk factors varies over time and they experience periods of underperformance relative to the broad market. Consequently all factor indices are exposed to relative risk (i.e. risk of underperforming the broad CW benchmark) in the short term which is shown by 'maximum relative drawdown' numbers.

3. Scientific Beta Multi-Strategy Factor Indices: Turning Risk into a Choice rather than a Fate

Also, one must not forget that Multi-Strategy factor indices have a limited set of securities to diversify across as they are constructed on 50% of the stock universe. This induces considerable tracking error relative to the broad CW index. However, this tracking error is not a drawback if associated outperformance is high enough, which is the case with Multi-Strategy factor indices, suggesting that they harvest the relevant factor premia in an efficient way. In fact, the results show that the information ratios of Multi-Strategy factor indices range from 0.47 for Low Volatility to 0.81 for Value.[11] We also report the historical probability of outperforming the benchmark. Across the four factors, the Multi-Strategy factor indices have higher outperformance probability than their CW counterparts.[12]

This outperformance of smart factor indices over traditional factor indices is not surprising. In fact a lack of diversification has been identified as a major drawback of CW indices. When it comes to factor tilted indices, Multi-Strategy factor indices show considerable improvement both over the broad cap-weighted index and over the CW factor index. We report the effective number of stocks (ENS)[13] which can be used as a measure of deconcentration. An index with balanced weights will have a high ENS. Going a step further and taking correlations into account, we also report the ratio of portfolio variance to the weighted variance of its constituents (GLR ratio of Goetzmann, Li and Rouwenhorst, 2005)[14] as a measure of diversification. A weighting scheme which exploits correlations to bring down portfolio's volatility will have a low GLR ratio.

The results in Exhibit 5 show that Multi-Strategy factor indices are in fact better diversified as they have considerably higher ENS and lower GLR ratio than their CW counterparts. On the other hand, CW factor indices display high GLR ratios and - with the exception of Mid Cap factor[15]– a low effective number of stocks, suggesting that while they may improve the exposure to rewarded risk factors compared to the broad cap-weighted index, they actually aggravate the concentration problem. In contrast, Multi-Strategy factor tilted indices obtain the desired factor tilts without undue concentration, which provides an explanation for their superior risk-adjusted performance.

11 - Within the framework of Smart Beta 2.0, one could choose to put tracking error constraints in smart factor indices. Details on relative risk control can be found at Goltz and Gonzalez (2013). However it is not desired because tracking error constraints increase the correlation among smart factor indices and thus reduce the diversification benefits upon their combination. A more practical approach to manage tracking error risk would be to put constraint on smart factor allocation rather than putting it on each smart factor index.
12 - We compute the frequency of obtaining positive excess returns if one invests in the strategy for a period of 3 or 5 years and is computed using a rolling window analysis with 1 week step size.
13 - The effective number of stocks (ENS) is defined as the reciprocal of the Herfindahl Index, which in turn is defined as the sum of squared weights across portfolio constituents. $ENS = 1/\sum_{i=1}^{N} W_i^2$ where N is the total number of stocks in the portfolio and W_i is the weight of i-th stock.
14 - Denoting RP the daily return series of an index, R_i is the daily return series of the i-th stock, and Wi the weight of i-th stock, the GLR ratio is defined as $Var(R_I)/\sum_{i=1}^{N} W_i.Var(R_i)$. Mid Cap selection picks up the bottom 250 market cap stocks in the broad USA universe. The weight profile of these stocks is flatter meaning that the difference in market cap of largest and small stock is not very high. Therefore Mid Cap CW index does not necessarily suffer from the problem of high concentration.
15 - Mid Cap selection picks up the bottom 250 market cap stocks in the broad USA universe. The weight profile of these stocks is flatter meaning that the difference in market cap of largest and small stock is not very high. Therefore Mid Cap CW index does not necessarily suffer from the problem of high concentration.

3. Scientific Beta Multi-Strategy Factor Indices: Turning Risk into a Choice rather than a Fate

Exhibit 5: Performance comparison of USA Cap Weighted Factor Indices and USA Multi-Strategy Factor Indices based on Scientific Beta Long Term Track Records – The exhibit shows the absolute performance, relative performance, and diversification indicators for Cap Weighted Factor Indices and Multi-Strategy Factor Indices for four factor tilts – mid cap, high momentum, low volatility, and value. Probability of outperformance is the historical empirical probability of outperforming the benchmark over a typical investment horizon of 3 or 5 years irrespective of the entry point in time. Maximum relative drawdown is the maximum drawdown of the long-short index whose return is given by the fractional change in the ratio of the strategy index to the benchmark index. GLR measure is defined as the ratio of the portfolio variance to the weighted variance of its constituents. The effective number of stocks (ENS) is defined as the reciprocal of the Herfindahl Index, which in turn is defined as the sum of squared weights of portfolio constituents. Complete stock universe consists of 500 largest stocks in USA. The benchmark is the cap-weighted portfolio of the full universe. The yield on secondary market US Treasury Bills (3M) is the risk-free rate. The return based analysis is based on daily total returns from 31/12/1972 to 31/12/2012 (40 years). All weight based statistics are average values across 160 quarters (40 years) from 31/12/1972 to 31/12/2012.

	Broad CW	Mid Cap		High Momentum		Low Volatility		Value	
		CW	Diversified Multi-Strategy	CW	Diversified Multi-Strategy	CW	Diversified Multi-Strategy	CW	Diversified Multi Strategy
Ann Returns	9.74%	12.54%	14.19%	10.85%	13.30%	10.09%	12.64%	11.78%	14.44%
Ann Volatility	17.47%	17.83%	16.73%	17.60%	16.30%	15.89%	14.39%	18.02%	16.55%
Sharpe Ratio	0.24	0.39	0.52	0.30	0.48	0.29	0.50	0.35	0.54
Historical Daily 5% VaR	1.59%	1.60%	1.50%	1.64%	1.50%	1.42%	1.28%	1.59%	1.47%
Max Drawdown	54.53%	60.13%	58.11%	48.91%	49.00%	50.50%	50.13%	61.20%	58.41%
Ann Excess Returns	-	2.80%	4.45%	1.10%	3.56%	0.35%	2.90%	2.04%	4.70%
Ann Tracking Error	-	5.99%	6.80%	3.50%	4.88%	4.44%	6.17%	4.74%	5.82%
95% Tracking Error	-	9.39%	11.56%	6.84%	8.58%	9.20%	11.53%	8.72%	10.14%
Information Ratio	-	0.47	0.66	0.32	0.73	0.08	0.47	0.43	0.81
Outperformance Probability (3Y)	-	70.08%	74.12%	78.21%	84.42%	50.10%	76.35%	69.82%	78.83%
Outperformance Probability (5Y)	-	75.33%	78.88%	86.76%	91.25%	54.27%	84.96%	72.05%	88.35%
Max Rel Drawdown	-	35.94%	42.06%	14.44%	17.28%	33.82%	43.46%	20.31%	32.68%
GLR	26.51%	19.12%	16.72%	28.52%	21.08%	29.60%	22.20%	26.46%	19.51%
Effective Number of Stocks	113	181	191	65	199	64	201	69	190

Exhibit 6 shows the Sharpe ratios and the Information ratios for factor indices from external commercial index providers, for CW factor indices, and for Scientific Beta USA Multi-Strategy factor indices. Against each competitor and for each factor tilt, the Scientific Beta Multi-Strategy factor indices perform better in both absolute and relative terms. For example Russell and MSCI Value indices have a Sharpe ratio of 0.27 as compared to 0.43 of Value Multi-Strategy index. The difference is even more striking in relative risk-adjusted performance levels, where the two competing indices have information ratios of -0.03 against 0.84 of the Value Multi-Strategy index. Similarly, Information ratios of Russell (0.05), S&P (-0.16) and MSCI (0.10) Low Volatility indices fall short when compared to the same for Low Volatility Multi-Strategy index in respective sub-periods.

Another interesting result brought to light by this analysis is that in about 50% of the cases, competing commercial factor indices exhibit lower Sharpe ratios than simple CW factor indices, which themselves have been shown to be poorly diversified. The competing factor indices show better Information ratio than CW factor indices in about 50% cases while Scientific Beta Multi-Strategy factor indices outperform CW factor indices in all the 12 cases analysed.

3. Scientific Beta Multi-Strategy Factor Indices: Turning Risk into a Choice rather than a Fate

Exhibit 6: Sharpe ratio and Information ratio of Competing Factor Indices – The table shows Sharpe ratios and Information ratios of Russell, S&P, and MSCI indices marketed as factor indices with the same performance metric for the corresponding Scientific Beta US Diversified Multi-Strategy and CW indices with stock selection based on mid cap, momentum, low volatility, and value, as well as the SciBeta Broad CW. All statistics are annualised and the analysis is based on daily total returns. Data is always taken for the ten-year period 31-Dec-2003 to 31-Dec-2013 as available on Bloomberg; Indices which have shorter than 10-year data available are compared for their respective period of data availability to broad CW, the corresponding tilted CW, and Smart Factor Index for the same period. MSCI® is a registered trademark of MSCI Inc. S&P® and S&P 500® are registered trademarks of Standard & Poor's Financial Services LLC ("S&P"), a subsidiary of The McGraw-Hill Companies, Inc. Russell 1000® and Russell® are registered trademarks of Russell Investments.

Provider	Tilt	Sharpe Ratio				Information Ratio			From	To	Full competitive index name
		Broad CW	Competitive Index	Tilted CW	SciBeta Diversified Multi-Strategy Index	Competitive Index	Tilted CW	SciBeta Diversified Multi-Strategy Index			
Russell	Low Vol	0.28	0.37	0.32	0.44	0.05	0.03	0.36	03/01/2005	31/12/2013	Russell 1000 Low Volatility
	Mid Cap	0.30	0.38	0.40	0.45	0.51	0.54	0.74	01/01/2004	31/12/2013	Russell Mid Cap
	Value	0.30	0.27	0.27	0.43	-0.03	-0.03	0.84	01/01/2004	31/12/2013	Russell 1000 Value
	Mom.	0.28	0.31	0.33	0.34	0.12	0.29	0.24	03/01/2005	31/12/2013	Russell US LC High Momentum
S&P	Low Vol	0.26	0.26	0.31	0.40	-0.06	0.07	0.31	31/03/2006	31/12/2013	S&P 1500 Reduced Volatility Tilt
	Mid Cap	0.30	0.38	0.40	0.45	0.39	0.54	0.74	01/01/2004	31/12/2013	S&P Mid Cap 400
	Value	0.26	0.27	0.18	0.29	0.19	-0.30	0.27	31/03/2006	31/12/2013	S&P 1500 Low Valuation Tilt
	Mom.	0.26	0.25	0.28	0.26	-0.10	0.10	-0.03	31/03/2006	31/12/2013	S&P 1500 Positive Momentum Tilt
MSCI	Low Vol	0.30	0.39	0.36	0.50	0.10	0.06	0.47	01/01/2004	31/12/2013	MSCI USA Minimum Volatility
	Mid Cap	0.30	0.35	0.40	0.45	0.41	0.54	0.74	01/01/2004	31/12/2013	MSCI USA Equal Weighted
	Value	0.30	0.27	0.27	0.43	-0.04	-0.03	0.84	01/01/2004	31/12/2013	MSCI USA Value Weighted
	Mom.	0.30	0.38	0.35	0.39	0.23	0.22	0.34	01/01/2004	31/12/2013	MSCI USA Momentum

3. Scientific Beta Multi-Strategy Factor Indices: Turning Risk into a Choice rather than a Fate

4. Assessing Robustness of Scientific Beta Multi-Strategy Factor Indices

4. Assessing Robustness of Scientific Beta Multi-Strategy Factor Indices

4.1 Implementation Concerns

Smart beta strategies, in their unaltered form often incur large turnover and are exposed to liquidity risk – the risk of investing substantial amount in illiquid stocks. Both these limitations could result in high transaction costs and other operational hurdles like large trading times while implementing the strategy. It should be noted that Scientific Beta indices are based on a universe of stocks belonging to the largest capitalisation range and that have been subjected to liquidity screens. Therefore liquidity issues are limited and smart beta strategies can be implemented with ease. To further improve the implementation, Scientific Beta follows turnover and capacity rules. The Scientific Beta Multi-Strategy factor index performance reported here relates to portfolios which have been subjected to turnover control[16] and capacity adjustments[17] which ensure easy implementation of these strategies. For a complete description of how the strategy is implemented we refer the reader to the Strategy Construction Rules of the Scientific Beta Indices available at www.scientificbeta.com.

Indeed, with the exception of momentum tilt, all smart factor indices have one-way annual turnover in the range of 22%-25%, which is well below the threshold of 30%.[18] Since Multi-Strategy factor indices aim to replace active style investing, impact of turnover on the performance, and not the absolute turnover, is the matter of concern. Transaction cost of 20 bps per 100% 1-W turnover represents the worst case observed historically and 100 bps represents an 80% reduction in market liquidity. The excess returns net of unrealistically high transaction costs, even for high momentum indices, remain quite significantly high.

Another wide-spread criticism of smart beta strategies is their limited capacity compared to the CW benchmark which by definition invests very small amounts in smaller and less liquid stocks. Exhibit 7 shows that the weighted average market capitalisation of factor indices ranges from $2.73 bn for Mid Cap Multi-Strategy index to $13.67 bn for Low Volatility Multi-Strategy index compared to $44.9 bn for the broad CW index. Another way to assess the impact of holding lesser liquid securities is to have an estimation of trading days to enter (or exit) the investment. 'Days to Trade' is average number of days required to trade total stock position in the portfolio of $1 bn, assuming that 100% of 'Average Daily Traded Volume (ADTV)' can be traded every day.[19] We report the 95th percentile of this statistic across all stocks and across all rebalancing dates[20] to get an estimate of extremely difficult trades.The results show that all Multi-Strategy factor indices have extreme trades which can be implemented within about 1/4th of a trading day.

16 - For Multi-Strategy factor indices, turnover is managed through optimal control of rebalancing of the indices - a technique based on rebalancing thresholds (see Leland, 1999; Martellini and Priaulet, 2002). At each quarterly rebalancing, the new optimised weights are implemented only 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 not 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 big impact on the strategy's performance. In the case of Diversified Multi-Strategy weighting scheme, the turnover control is applied to the five constituent strategies before combining them.
17 - The following capacity rules are applied to limit liquidity issues that may arise upon investing and upon rebalancing. 1. Holding Capacity Rule - the weight of each stock is capped to avoid large investment in the smallest stocks. 2. Trading Capacity Rule - the change in weight of each stock is capped to avoid large trading in small illiquid stocks at the rebalancing. Formally, we adjust weights so that $W_{i,I} \leq 10.W_{i,CW}\ \forall\ i \in [1, N]$ and $\Delta W_{i,I} \leq W_{i,CW}\ \forall\ i \in [1, N]$, where $W_{i,I}$ is the weight of i-th stock in the Multi-Strategy factor index and $W_{i,CW}$ is the weight if same stock in a cap-weighted index that comprises of the same stocks as the Multi-Strategy factor index in question.
18 - Momentum strategies typically result in high turnover (Chan *et al.*, 1999). Momentum chasing strategies have short time horizon because persistence in price movement is a short-term phenomenon and mean-reversion is observed in longer horizons. Therefore to extract momentum premium, momentum score assignment is done semi-annually which results in higher turnovers.
19 - Even if one assumes that only about 10% of average daily traded volume can be traded, one would still get a very reasonable 'Days to Trade' number for the smart factor indices.
20 - The measure is computed for all stocks at each rebalancing in the last 10 years (40 quarters) and the 95th percentile is reported.

4. Assessing Robustness of Scientific Beta Multi-Strategy Factor Indices

Exhibit 7: Implementation Costs of USA Multi-Strategy Factor Indices based on Scientific Beta Long Term Track Records
The exhibit shows weighted average market cap, turnover, and outperformance net of transaction costs of Multi-Strategy Factor Indices for four factor tilts – mid cap, high momentum, low volatility, and value. Probability of outperformance is the historical empirical probability of outperforming the benchmark over a typical investment horizon of 3 or 5 years irrespective of the entry point in time. Maximum relative drawdown is the maximum drawdown of the long-short index whose return is given by the fractional change in the ratio of the strategy index to the benchmark index. GLR measure is defined as the ratio of the portfolio variance to the weighted variance of its constituents. The effective number of stocks (ENS) is defined as the reciprocal of the Herfindahl Index, which in turn is defined as the sum of squared weights of portfolio constituents. Complete stock universe consists of 500 largest stocks in USA. The benchmark is the cap-weighted portfolio of the full universe. The yield on secondary market US Treasury Bills (3M) is the risk-free rate. The return based analysis is based on daily total returns from 31/12/1972 to 31/12/2012 (40 years). All weight based statistics are average values across 160 quarters (40 years) from 31/12/1972 to 31/12/2012.

	USA Broad CW	USA Diversified Multi-Strategy			
		Mid Cap	High Momentum	Low Volatility	Value
Ann. 1-Way Turnover	2.65%	23.73%	63.46%	25.75%	23.83%
Relative Returns	-	4.45%	3.56%	2.90%	4.70%
Rel Returns net of 20 bps transaction costs	-	4.41%	3.43%	2.85%	4.65%
Rel Returns net of 100 bps transaction costs	-	4.22%	2.92%	2.65%	4.46%
Weighted Avg Mkt Cap ($m)	44 959	2 734	12 786	13 666	8 326
Days to Trade $1 bn Investment (95% quintile)	0.03	0.24	0.18	0.20	0.19

We show above that Multi-Strategy factor indices in the USA universe, which are based on 500 largest stocks, do not show any significant illiquidity that could hinder smooth implementation of the strategy. However, it is interesting to assess whether liquidity can be further improved. We thus construct high liquidity versions of the same portfolios by selecting the top 60% of stocks by liquidity among the stocks included in the factor tilted portfolios. Exhibit 8 displays performance and risk characteristics of the resulting High Liquidity Multi-Strategy factor indices. As expected, weighted average market cap and 'Days to Trade' numbers show significant improvement. Furthermore, the indices maintain most of the outperformance of the original portfolios even though outperformance is reduced by a few basis points which can be explained by a potential illiquidity premium (Xiong *et al.*, 2009).

Exhibit 8: Performance of USA High Liquidity Multi-Strategy Factor Indices based on Scientific Beta Long Term Track Records
The exhibit shows weighted average market cap, turnover, and outperformance net of transaction costs of High Liquidity Multi-Strategy Factor Indices for four factor tilts – mid cap, high momentum, low volatility, and value. Probability of outperformance is the historical empirical probability of outperforming the benchmark over a typical investment horizon of 3 or 5 years irrespective of the entry point in time. Maximum relative drawdown is the maximum drawdown of the long-short index whose return is given by the fractional change in the ratio of the strategy index to the benchmark index. GLR measure is defined as the ratio of the portfolio variance to the weighted variance of its constituents. The effective number of stocks (ENS) is defined as the reciprocal of the Herfindahl Index, which in turn is defined as the sum of squared weights of portfolio constituents. Complete stock universe consists of 500 largest stocks in USA. The benchmark is the cap-weighted portfolio of the full universe. The yield on secondary market US Treasury Bills (3M) is the risk-free rate. The return based analysis is based on daily total returns from 31/12/1972 to 31/12/2012 (40 years). All weight based statistics are average values across 160 quarters (40 years) from 31/12/1972 to 31/12/2012.

	USA Broad CW	USA High Liquidity Diversified Multi-Strategy			
		Mid Cap	High Momentum	Low Volatility	Value
Ann Returns	9.74%	14.02%	12.54%	11.83%	13.84%
Ann Volatility	17.47%	17.82%	17.06%	14.91%	17.06%
Sharpe Ratio	0.24	0.48	0.41	0.42	0.49
Historical Daily 5% VaR	1.59%	1.59%	1.58%	1.33%	1.51%
Max Drawdown	54.53%	59.49%	49.61%	50.25%	57.98%

4. Assessing Robustness of Scientific Beta Multi-Strategy Factor Indices

Ann Excess Returns	-	4.28%	2.80%	2.09%	4.10%
Ann Tracking Error	-	6.93%	4.47%	5.71%	5.47%
95% Tracking Error	-	12.11%	8.11%	11.41%	9.31%
Information Ratio	-	0.62	0.63	0.37	0.75
Outperformance Probability (3Y)	-	75.10%	92.75%	73.14%	79.19%
Outperformance Probability (5Y)	-	80.85%	97.16%	76.37%	87.86%
Max Rel Drawdown	-	36.29%	11.12%	40.95%	26.67%
GLR	26.51%	17.64%	23.31%	24.63%	21.65%
Effective Number of Stocks	113	115	120	122	118
Ann. 1-Way Turnover	2.65%	30.87%	66.37%	27.30%	27.46%
Rel Returns net of 20 bps transaction costs	-	4.22%	2.67%	2.03%	4.04%
Rel Returns net of 100 bps transaction costs	-	3.97%	2.14%	1.81%	3.82%
Weighted Avg Mkt Cap ($m)	44 959	3 293	18 513	19 691	11 683
Days to Trade $1 bn Investment (95% quintile)	0.03	0.24	0.12	0.15	0.13

4.2 Conditional Performance

As discussed before, the rewarded factors yield premium in long term in exchange of risks that can lead to considerable underperformance or relative drawdowns in smaller periods. Therefore it is important to analyse time varying performance of Multi-Strategy factor indices in an attempt to identify and characterise the nature of risk premium. One approach is to use NBER definition of business cycle to breakdown the analysis period into alternating sub-periods of 'contraction' and 'expansion' phases. In addition to economic cycles, equity market conditions such as bullish or bearish markets may have a considerable impact on how different portfolio strategies perform. For example, Amenc *et al.*, 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. Moreover, 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. It is therefore important to assess the robustness of performance with respect to such conditions.

Exhibit 9 shows annualised excess returns of the four Multi-Strategy factor indices over broad CW index in different business cycles and different equity market conditions. It shows that the performance of Multi-Strategy factor indices depends on market conditions. For example, the Mid Cap Multi-Strategy index post much higher outperformance in bull markets (+5.37%) than in bear markets (+3.02%). The converse is true for Low Volatility Multi-Strategy index which underperforms by 0.81% in bull markets and outperforms by 7.33% in bear markets. Similarly, the Mid Cap Multi-Strategy index has outperformed by a larger margin in expansion phases while the Low Volatility Multi-Strategy index was favoured by contraction phases. This difference in sensitivities to market conditions suggests

4. Assessing Robustness of Scientific Beta Multi-Strategy Factor Indices

room for improvement through allocating across multiple Multi-Strategy factor indices, and issue we turn to in the next subsection.

Exhibit 9: Conditional Performance of USA Multi-Strategy Factor Indices based on Scientific Beta Long Term Track Records
The exhibit shows relative performance of Multi-Strategy Factor Indices for four factor tilts – mid cap, high momentum, low volatility, and value in two distinct market conditions – bull markets and bear markets and in contraction and expansion phases of US economy (NBER). Calendar quarters with positive market index returns comprise bull markets and the rest constitute bear markets. Complete stock universe consists of 500 largest stocks in 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).

	USA Diversified Multi-Strategy			
	Mid Cap	High Momentum	Low Volatility	Value
Bull Markets				
Ann Relative Returns	5.37%	3.44%	-0.81%	3.89%
Ann Tracking Error	5.86%	4.10%	5.17%	5.08%
Information Ratio	0.92	0.84	-0.16	0.77
Bear Markets				
Ann Relative Returns	3.02%	3.43%	7.33%	5.33%
Ann Tracking Error	8.41%	6.20%	7.84%	7.10%
Information Ratio	0.36	0.55	0.93	0.75
NBER Contraction Phases				
Ann Relative Returns	6.12%	4.03%	5.39%	4.70%
Ann Tracking Error	9.18%	7.00%	7.70%	7.78%
Information Ratio	0.67	0.58	0.70	0.60
NBER Expansion Phases				
Ann Relative Returns	4.10%	3.45%	2.39%	4.69%
Ann Tracking Error	6.28%	4.40%	5.86%	5.40%
Information Ratio	0.65	0.78	0.41	0.87

4.3 Comparison across Regions

Having shown the robustness of Multi-Strategy factor indices using US long-term track records, we test the consistency of their performance across different developed stock markets. Due to limited availability to reliable data for non-US markets the time period of analysis is 31 December 2003 to 31 December 2013 (10 years). The Multi-Strategy factor indices and CW indices are governed by the same methodology as described for the USA data, and the only difference across regions is the number of stocks. Stock universe sizes for developed regions are: USA (500), Eurozone (300), UK (100), Japan (500), and Asia Pacific ex Japan (400).

Exhibit 10 shows that all ERI Scientific Beta Multi-Strategy factor indices exhibit superior Sharpe ratios than both the broad CW index and their respective CW factor indices. Information ratios of the four Multi-Strategy factor indices are usually higher than those of CW factor indices and often reach impressive levels such as 0.84 for USA Value and 0.69 for UK Momentum. Since analysis period is very short, certain CW factor indices in certain regions do not necessary outperform the broad CW index despite being tilted towards the long-term rewarded factors – the problem of sample time

4. Assessing Robustness of Scientific Beta Multi-Strategy Factor Indices

dependency. For example, Japan High Momentum CW and UK Value CW indices have excess return of -0.45% and -2.27% respectively in the 10-year period. The benefit from using a well-diversified weighting scheme is more visible in these cases as their corresponding Multi-Strategy factor indices outperform by 1.22% and 1.77%.

Exhibit 10: Performance of Scientific Beta Multi-Strategy Factor Indices in developed markets
The exhibit shows the absolute and relative performance of Multi-Strategy Factor Indices in 5 developed regions for four factor tilts – mid cap, high momentum, low volatility, and value. Developed universes and their respective stock universe sizes are: USA (500), Eurozone (300), UK (100), Japan (500), and Developed Asia Pacific ex-Japan (400). Benchmark is the Cap-Weighted index on the full universe for each region. Risk-free rate used for these regions is Secondary Market US T-bill (3M), Euribor (3M), UK T-bill (3M), Japan Gensaki T-bill (1M) and Secondary Market US T-bill (3M) respectively. All statistics are annualised. The analysis is based on daily total returns from 31/12/2003 to 31/12/2013 (10 years).

	Broad CW	Mid Cap		High Momentum		Low Volatility		Value	
		CW	Diversified Multi-Strategy	CW	Diversified Multi-Strategy	CW	Diversified Multi-Strategy	CW	Diversified Multi-Strategy
USA									
Ann Returns	7.68%	10.41%	10.80%	8.64%	9.40%	7.94%	10.08%	7.56%	10.54%
Ann Volatility	20.23%	22.33%	20.29%	20.38%	20.07%	17.82%	16.99%	22.46%	20.63%
Sharpe Ratio	0.30	0.40	0.45	0.35	0.39	0.36	0.50	0.27	0.43
Ann Rel Returns	-	2.73%	3.12%	0.96%	1.72%	0.26%	2.40%	-0.12%	2.86%
Ann Tracking Error	-	5.07%	4.23%	4.29%	5.07%	4.05%	5.15%	4.04%	3.41%
Information Ratio	-	0.54	0.74	0.22	0.34	0.06	0.47	-0.03	0.84
Eurozone									
Ann Returns	6.35%	7.99%	8.41%	9.09%	10.60%	8.39%	9.19%	6.09%	7.68%
Ann Volatility	20.58%	18.63%	16.69%	19.74%	16.66%	18.35%	14.96%	22.81%	20.26%
Sharpe Ratio	0.21	0.32	0.38	0.35	0.51	0.34	0.47	0.18	0.28
Ann Rel Returns	-	1.64%	2.05%	2.73%	4.25%	2.04%	2.84%	-0.26%	1.33%
Ann Tracking Error	-	6.28%	7.07%	4.82%	7.05%	4.48%	7.27%	3.96%	4.55%
Information Ratio	-	0.26	0.29	0.57	0.60	0.45	0.39	-0.07	0.29
UK									
Ann Returns	8.32%	11.76%	11.10%	9.46%	12.71%	8.19%	11.86%	6.04%	10.09%
Ann Volatility	19.18%	19.67%	17.95%	20.57%	17.99%	16.57%	15.33%	21.35%	19.43%
Sharpe Ratio	0.30	0.46	0.47	0.33	0.56	0.34	0.60	0.16	0.38
Ann Rel Returns	-	3.44%	2.78%	1.14%	4.39%	-0.13%	3.54%	-2.27%	1.77%
Ann Tracking Error	-	7.17%	7.29%	5.95%	6.37%	5.53%	7.60%	4.93%	5.78%
Information Ratio	-	0.48	0.38	0.19	0.69	-0.02	0.47	-0.46	0.31
Japan									
Ann Returns	4.09%	4.97%	5.72%	3.64%	5.31%	5.34%	7.15%	5.65%	6.86%
Ann Volatility	22.62%	21.21%	19.26%	22.39%	19.95%	19.50%	17.42%	22.60%	20.15%
Sharpe Ratio	0.17	0.23	0.29	0.15	0.26	0.26	0.40	0.24	0.33
Ann Rel Returns	-	0.89%	1.64%	-0.45%	1.22%	1.26%	3.06%	1.56%	2.77%
Ann Tracking Error	-	6.62%	7.73%	5.28%	7.48%	5.95%	8.65%	3.84%	6.22%
Information Ratio	-	0.13	0.21	-0.09	0.16	0.21	0.35	0.41	0.45
Developed Asia Pacific ex Japan									
Ann Returns	12.91%	15.31%	15.91%	16.12%	18.01%	13.86%	14.24%	14.92%	16.82%
Ann Volatility	23.93%	23.08%	20.72%	25.45%	22.13%	22.85%	17.74%	24.36%	21.93%
Sharpe Ratio	0.47	0.60	0.69	0.57	0.74	0.54	0.71	0.55	0.70
Ann Rel Returns	-	2.40%	2.99%	3.21%	5.10%	0.94%	1.33%	2.01%	3.91%
Ann Tracking Error	-	6.98%	7.55%	4.73%	6.85%	4.05%	8.21%	5.70%	6.77%
Information Ratio	-	0.34	0.40	0.68	0.74	0.23	0.16	0.35	0.58

5. Usage of Scientific Beta Multi-Strategy Factor Indices

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Risk factors carry time varying risk premia (Asness *et al.*, 1992), Cohen, Polk, and Vuolteenaho, 2003). Also in the previous section, we found that the performance of Multi-Strategy factor indices depends on market conditions, and that a period favourable to one factor may be detrimental to another. Allocating across factors may thus allow investors to diversify the sources of their outperformance and smooth their performance across market conditions. Investors may use allocation across factor tilts to target an absolute (Sharpe ratio, Volatility) or relative risk (Information ratio, Tracking Error with respect to broad CW index) objective. To illustrate the potential of multi-factor allocations, we draw on two standard multi-beta allocations, which correspond to multi-beta multi-strategy indices published by ERI Scientific Beta, notably Equal Weight (EW) and Equal Risk Contribution (ERC) to smart factor indices tilted to the four main risk factors. The Equal Weight allocation, which is a simple and robust allocation in terms of absolute risk, invests ¼ in each of the four Multi-Strategy factor indices. The Equal Risk Contribution allocation combines the four Multi-Strategy factor indices so as to equalise their contributions to the tracking error risk. This method is the relative risk version of the ERC approach of Maillard *et al.* (2010), who equalise the contribution to portfolio volatility.

Exhibit 11 summarises the performance of Multi-Beta Multi-Strategy EW and Multi-Beta Multi-Strategy ERC indices. Due to relatively lower levels of tracking error, these Multi-Beta Multi-Strategy indices exhibit higher Information ratios and higher outperformance probabilities than their average component smart factor index (compare Exhibit 5). Another important consequence of combining factor tilts is that Multi-Beta Multi-Strategy indices mitigate the risk of choosing a single factor index and produce more stable outperformance across bull and bear markets, with information ratios that are almost indistinguishable in bull and bear markets. From an implementation perspective, the multi-factor allocations lower the turnover relative to the average turnover of their component indices as some of the trades cancel across the different factor tilts. Allocation across several smart factor indices thus offers both implementation and performance benefits. While the construction of a multi-factor benchmark ultimately depends on an investor's selection of factors and a choice of a suitable allocation method which take into account his context and constraints, the illustrative examples below provide evidence that well-diversified factor indices can be employed as suitable building blocks to harvest additional benefits from multi-factor allocation decisions.

5. Usage of Scientific Beta Multi-Strategy Factor Indices

Exhibit 11: Performance of USA Multi-Beta Multi-Strategy Indices based on Scientific Beta Long Term Track Records
The exhibit shows the absolute performance, relative performance, diversification indicators, and implementation costs of Multi-Beta Multi-Strategy EW Index and Multi-Beta Multi-Strategy ERC Index. Complete stock universe consists of 500 largest stocks in USA. The benchmark is the cap-weighted portfolio of the full universe. The yield on secondary market US Treasury Bills (3M) is the risk-free rate. All statistics are annualised. The return based analysis is based on daily total returns from 31/12/1972 to 31/12/2012 (40 years). All weight based statistics are average values across 160 quarters (40 years) from 31/12/1972 to 31/12/2012.

	Broad CW	USA Multi-Beta Diversified Multi-Strategy	
		Equal Weighted (EW) Allocation	Equal Risk Contribution (ERC) Allocation
Ann Returns	9.74%	13.72%	13.53%
Ann Volatility	17.47%	15.75%	15.69%
Sharpe Ratio	0.24	0.52	0.51
Ann Excess Returns	-	3.98%	3.79%
Ann Tracking Error	-	5.23%	4.91%
95% Tracking Error	-	8.95%	8.11%
Information Ratio	-	0.76	0.77
Outperformance Probability (3Y)	-	80.38%	80.90%
Outperformance Probability (5Y)	-	90.10%	90.32%
Max Rel Drawdown	-	33.65%	28.74%
GLR	26.51%	18.86%	19.29%
Effective Number of Stocks	113	318	312
Ann. 1-Way Turnover	2.65%	28.94%	31.53%
Rel Returns net of 20 bps transaction costs	-	3.92%	3.73%
Rel Returns net of 100 bps transaction costs	-	3.69%	3.47%
Weighted Avg Mkt Cap ($m)	44 959	9 378	10 280
Days to Trade $1 bn Investment (95% quintile)	0.03	0.12	0.12
Bull Markets			
Ann Relative Returns	-	3.03%	2.92%
Ann Tracking Error	-	4.45%	4.20%
Information Ratio	-	0.68	0.69
Bear Markets			
Ann Relative Returns	-	4.83%	4.56%
Ann Tracking Error	-	6.57%	6.12%
Information Ratio	-	0.74	0.74

5. Usage of Scientific Beta Multi-Strategy Factor Indices

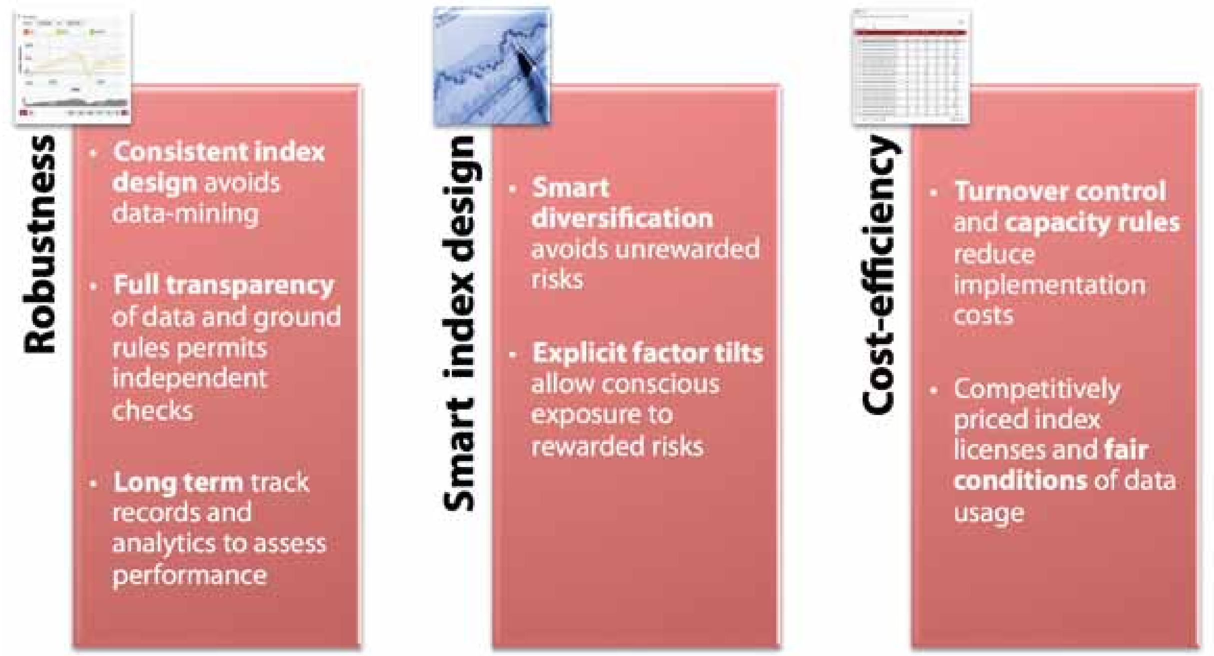
Conclusions

Conclusions

Current smart beta investment approaches only provide a partial answer to the main shortcomings of cap-weighted indices. ERI Scientific Beta Multi-Strategy factor indices – which diversify away unrewarded risks and seek exposure to rewarded risk factors – simultaneously address the two main problems of cap-weighted indices (their undesirable factor exposures and their heavy concentration). The adoption of simple and consistent portfolio construction methodology by ERI Scientific Beta, also termed as smart factor investing, avoids data mining risks.

The results suggest that such Multi-Strategy factor indices lead to considerable improvements in risk-adjusted performance. For long term US data, smart factor indices for a range of different factor tilts roughly double the Sharpe ratio of the broad cap-weighted index. Moreover, outperformance of such indices persists at levels ranging from 2.92% to 4.46%, even when assuming unrealistically high transaction costs. Outperformance of Multi-Strategy factor indices over CW factor indices is observed for other developed stock markets as well. By providing explicit tilts to consensual factors, such indices improve upon many current smart beta offerings, where more often than not factor tilts result as unintended consequences of ad hoc methodologies.

Exhibit 12: Summary of Advantages of Scientific Beta Multi-Strategy Factor Indices



Investors may employ Scientific Beta Multi-Strategy factor indices as high performance building blocks to their portfolios in a variety of contexts. First, single factor tilts may be used as substitutes for actively managed or passive cap-weighted portfolios with the same factor tilt. For example, one may consider replacing a mandate tracking a cap-weighted value index with one tracking the Scientific Beta Value Multi-Strategy Index. Second, smart factor indices for a single factor tilt may be used as a complement. For instance, one may usefully complement a value-oriented actively

Conclusions

managed portfolio or a value-oriented alternative index portfolio (such as a fundamentally weighted portfolio) through a smart factor index representing a complementary tilt (e.g. momentum or low vol). Third, smart factor indices are natural building blocks for multi-factor allocations. Indeed, Exhibit 16 has shown that multi-factor allocations in the form of Scientific Beta Multi-Beta Multi-Strategy indices lead to pronounced improvements in risk-adjusted returns when combining factors which have low correlation with each other, as well as significant easing of implementation through internal crossing of trades across different factor tilts. In practice, one could further add value over the allocations described in this paper by taking into account the investor's constraints, liabilities and broad investment context in custom smart beta allocations.

Conclusions

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About ERI Scientific Beta

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A "More for Less" Initiative for Smart Beta Investing

More Academic Rigour, More Transparency, More Choice, More Analytics, More Risk Control, Less Expensive

ERI Scientific Beta aims to be the first provider of a smart beta indices platform to help investors understand and invest in advanced beta equity strategies. It has three principles:

- **Choice:** A multitude of strategies are available allowing users to build their own benchmark, choosing the risks to which they wish, or do not wish, to be exposed. This approach, which makes investors responsible for their own risk choices, referred to as Smart Beta 2.0, is the core component of the index offerings proposed by ERI Scientific Beta.

- **Transparency:** The rules for all of the Scientific Beta series are replicable and transparent. The track records of the Scientific Beta indices can be checked and justified through unrestricted access to historical compositions.

- **Clarity:** Exhaustive explanations of construction methodologies are provided, as well as detailed performance and risk analytics.

Established by EDHEC-Risk Institute, one of the very top academic institutions in the field of fundamental and applied research for the investment industry, ERI Scientific Beta shares the same concern for scientific rigour and veracity, which it applies to all the services that it offers investors and asset managers.

Part of EDHEC Business School, a not-for-profit organisation, EDHEC-Risk Institute has sought to provide the ERI Scientific Beta services in the best possible economic conditions.

The ERI Scientific Beta offering covers three major services:

- **Scientific Beta Indices**

Scientific Beta Indices are smart beta indices that aim to be the reference for the investment and analysis of alternative beta strategies. Scientific Beta Indices reflect the state-of-the-art in the construction of different alternative beta strategies and allow for a flexible choice among a wide range of options at each stage of their construction process. This choice enables users of the platform to construct their own benchmark, thus controlling the risks of investing in this new type of beta (Smart Beta 2.0). The Scientific Beta platform is currently offering 2,916 smart beta indices.

- **Scientific Beta Analytics**

Scientific Beta Analytics are detailed analytics and exhaustive information on its smart beta indices to allow investors to evaluate the advanced beta strategies in terms of risk and performance. The analytics capabilities include risk and performance assessments, factor and sector attribution, and relative risk assessment. Scientific Beta Analytics also allow the liquidity, turnover and diversification quality of the indices offered to be analysed. In the same way, analytics provide an evaluation of the probability of out-of-sample outperformance of the various strategies present on the platform.

About ERI Scientific Beta

We believe that it is important for investors to be able to conduct their own analyses, select their preferred time period and choose among a wide range of analytics in order to produce their own picture of strategy performance and risk.

- **Scientific Beta Fully-Customised Benchmarks**

The Scientific Beta Fully-Customised Benchmarks service enables investors and asset managers to benefit from its expertise and the ability to determine and implement their choice of stocks, weighting schemes, and absolute and relative risk constraints in keeping with their objectives.

With a concern to provide worldwide client servicing, ERI Scientific Beta is present in Boston, London, Nice, Singapore and Tokyo.

ERI Scientific Beta has a dedicated team of 35 people who cover not only client support from Nice, Singapore and Boston, but also the development, production and promotion of its index offering.

About ERI Scientific Beta

ERI Scientific Beta Publications

ERI Scientific Beta Publications

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