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Scientific Beta

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Scientific Beta Multi-Beta Multi-Strategy Indices: Implementing Multi-Factor Equity Portfolios with Smart Factor Indices

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Abstract

Leading academic studies demonstrate that value, momentum, small cap and low-volatility stocks systematically generate higher risk-adjusted returns and are well rewarded in the long term. Hence, these sources of outperformance have been called factors, and the strategic allocation towards factors, factor investing. Even though factor investing is based on rational investment, and seems to be quite natural, it has only recently come into the spotlight, both from an academic perspective and a practitioner standpoint. Thus, investors are currently facing new questions: Which factors should they choose to tilt towards? How do they best extract the premium that the factors carry? And finally, once the last two have been answered, how can they allocate across factors to reach specific investment objectives? Factor indices have come to be considered as a cost efficient, straightforward and transparent way to implement factor allocations. We illustrate in this paper why it makes sense to allocate across different factors, and show the sizable performance using ERI Scientific Beta's Multi-Beta Multi-Strategy EW and ERC Indices, which are an equal-weighted allocation and an equal (relative) risk contribution allocation to smart factor indices. Furthermore, we examine the robustness of these multi-factor allocations and the implementation benefits that stem from multi-factor equity portfolios. We demonstrate that exposure to various factors whose premia behave differently over time and across market conditions translate into smoother outperformance. Furthermore, natural crossing benefits bring down the turnover of multi-beta indices compared to the same allocation managed in separate single-factor mandates.

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Introduction - The Recent Trend of Factor Investing Raises New Questions

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Sophisticated institutional investors have increasingly started to review factor-based equity investment strategies. For example, the Parliament of Norway, which acts as a trustee for the Norwegian Oil Fund,[1] 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 (CW) benchmark of the fund's actively-managed portfolio 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 towards and make explicit decisions on these tilts. This discussion of active managers' sources of outperformance has naturally led to factor indices being considered as a more cost efficient, straightforward and transparent way of implementing such factor tilts. Investors need to ask three main questions when considering such factor-based equity investing strategies.

The first question investors face when wanting to benefit from factor investing is to determine which factors to select. In order to avoid the pitfalls of non-persistent factor premia and achieve robust performance, investors should keep the following checks in mind. First, they should require a sound economic rationale for the existence and persistence of a positive premium. Second, due to the risks of data-mining, investors would be well-advised to stick to simple factor definitions that are widely used in the literature rather than rely on complex and proprietary factor definitions (Van Gelderen and Huij, 2013).

However, having access to a 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 risks (due to excessive concentration, for instance). A second relevant question is thus how to best extract the premium for a factor in an efficient way. Amenc et al. (2014a) address this question in detail. The authors present how the Smart Beta 2.0 approach (Amenc et al., 2013), whose main idea is to apply a smart weighting scheme to an explicit selection of stocks, enables the construction of factor indices which are not only exposed to the desired risk factors, but also avoid being exposed to unrewarded risks. This approach, referred to as "smart factor indices" can be summarised as follows. In a nutshell, the explicit selection of stocks provides the desired tilt (i.e. the beta), while the smart weighting scheme addresses concentration issues and diversifies away specific and unrewarded risks.

A third 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 paper to provide an exhaustive framework for factor allocation, we illustrate the use of factor indices in two different allocation contexts – one aiming to improve absolute risk-adjusted returns, and one targeting relative risk objectives.

1 - See Chambers, Dimson and Ilmanen (2012) for more details about the "Norway model" and Koedijk, Slager and Stork (2014) on how to address practical challenges faced by institutional investors when integrating factor investing into their investment process.

Introduction - The Recent Trend of Factor Investing Raises New Questions

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,[2] 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.*, 2012a).[3]

2 - 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).
3 -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.

Introduction - The Recent Trend of Factor Investing Raises New Questions

1. The Rationale for Multi-Factor Allocation: Why Combine Factor Indices?

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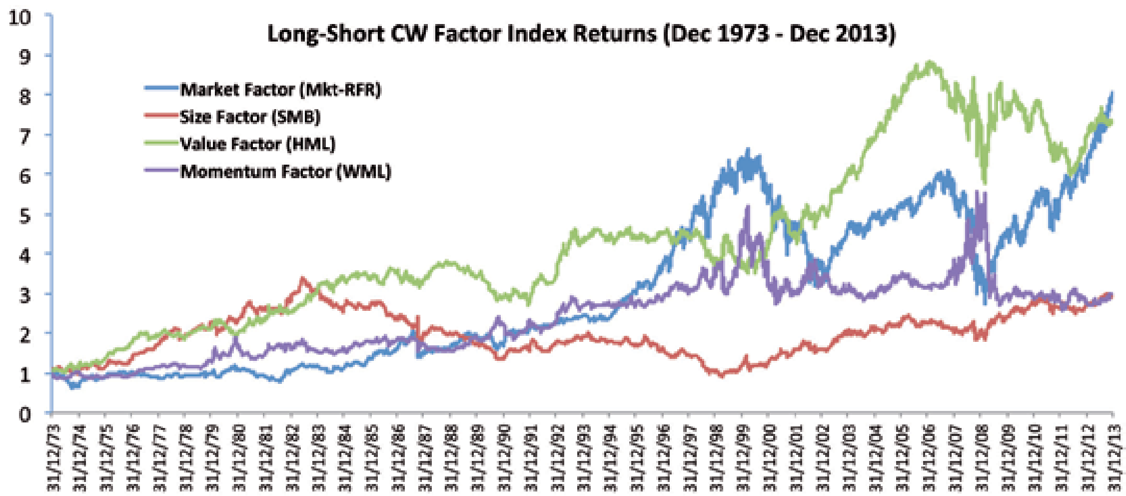
Using smart beta indices as well-diversified ingredients that provide exposure to desired risk factors, we now analyse the potential benefits of combining factor tilts ("multi-beta allocations").

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 (see Exhibit 1 for an illustration of the different cyclicality of typical long-short factors), allocating across factors allows investors to diversify the sources of their outperformance and smooth their performance across market conditions. In brief, the cyclicality of returns differs from one factor to another (i.e. the different factors work at different times).

Exhibit 1: Cyclicality of the Factors – US Example
The plot shows for each factor through the 40-year history the cumulative index returns of Long Short CW Factors. Factors are based on SciBeta US Long Term Track Records. The Market factor is the daily return of the cap-weighted index of all stocks that constitute the index portfolio in excess of the risk-free rate. Small size factor is the daily return series of a cap-weighted portfolio that is long the smallest 30% of stocks (by market cap) and short the largest 30% of stocks (by market cap) of the extended universe (i.e. including small caps). Value factor is the daily return series of a cap-weighted portfolio that is long the highest 30% and short the lowest 30% of stocks by B/M ratio in the investable universe. Momentum factor is the daily return series of a cap-weighted portfolio that is long the 30% highest and short the 30% lowest 52 weeks (minus most recent 4 weeks) past return stocks in the investable universe. The "Secondary Market US Treasury Bills (3M)" is the risk-free rate in US Dollars. All statistics are annualised. The analysis is based on daily total returns from 31/12/1973 to 31/12/2013.



Intuitively, we would expect pronounced allocation benefits across factors which have low correlation with each other. As shown in Exhibit 2, the correlation of the relative returns of the four smart factor indices over the cap-weighted benchmark is far below one. Importantly, this indicates that a combination of these indices would significantly lower the overall tracking error of the portfolio. Exhibit 2 shows the same analysis done conditionally for either bull or bear market regimes leads to similar results, meaning that diversification benefits do exist independently from the market

1. The Rationale for Multi-Factor Allocation: Why Combine Factor Indices?

regime. This is consistent with research findings in asset allocation studies. For instance, Ilmanen and Kizer (2012) have shown 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.

Exhibit 2: 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 1973 to 31 December 2013 (40 years) in panel A and from 31 December 2003 to 31 December 2013 (10 years) in panel B. In panels C and D, the analysis is conducted conditional on the market regime being bull or bear. Calendar quarters with positive market index returns comprise bull markets and the rest constitute bear markets. 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 (Dec 1973-Dec 2013)		Diversified Multi-Strategy			
		Low Volatility	Mid Cap	Value	Momentum
Diversified Multi-Strategy	Low Volatility	1	0.64	0.71	0.63
	Mid Cap		1	0.86	0.69
	Value			1	0.65
	Momentum				1

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

SciBeta Investable Developed Indices (Dec 2003 – Dec 2013)		Diversified Multi-Strategy			
		Low Volatility	Mid Cap	Value	Momentum
Diversified Multi-Strategy	Low Volatility	1	0.53	0.26	0.45
	Mid Cap		1	0.49	0.66
	Value			1	0.17
	Momentum				1

Panel C –Bull/Bear Markets Relative Returns Correlation Matrix - US Long Term Track Records

US Long Term Track Records (Dec 1973-Dec 2013)									
Bull Markets		Diversified Multi-Strategy			Bear Markets		Diversified Multi-Strategy		
		Mid Cap	Value	Momentum			Mid Cap	Value	Momentum
Diversified Multi-Strategy	Low Volatility	0.62	0.69	0.62	Diversified Multi-Strategy	Low Volatility	0.67	0.73	0.64
	Mid Cap		0.86	0.69		Mid Cap		0.87	0.69
	Value			0.67		Value			0.64

Panel D - Bull/Bear Markets Relative Returns Correlation Matrix - SciBeta Global Developed Indices

SciBeta Investable Developed Indices (Dec 2003 – Dec 2013)									
Bull Markets		Diversified Multi-Strategy			Bear Markets		Diversified Multi-Strategy		
		Mid Cap	Value	Momentum			Mid Cap	Value	Momentum
Diversified Multi-Strategy	Low Volatility	0.53	0.17	0.55	Diversified Multi-Strategy	Low Volatility	0.53	0.34	0.37
	Mid Cap		0.47	0.72		Mid Cap		0.50	0.61
	Value			0.23		Value			0.11

1. The Rationale for Multi-Factor Allocation: Why Combine Factor Indices?

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 weight in the momentum-tilted portfolio will tend to increase at the same time their weight in the value-tilted portfolio will tend to decrease. The effects will not be completely cancelled out, 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.

2. Performance Benefits of Allocating Across Factors

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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. In Exhibit 3, we show 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 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 of allocation with a relative risk objective consistent with risk-parity investing.[4] 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 indices) can be deployed using smart factor indices as ingredients to reach more specific investment objectives (see Amenc *et al.*, 2014b).

Exhibit 3 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 they exhibit 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 a higher Sharpe ratio (0.62 in the US, 0.56 in the Developed universe) which, compared to the broad cap-weighted reference (0.32 in the US, and 0.36 in Developed universe), represents a relative Sharpe ratio gain of 94% 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 for the reduction of tracking error 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 represents 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 0.79 and 0.80 from an average information ratio for the constituent indices of 0.69 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). 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.

4 - 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. See Appendix A1 for more details.

2. Performance Benefits of Allocating Across Factors

Exhibit 3: Performances and Risks of Multi-Beta Multi-Strategy Allocations vs. Single Factor Tilts
The table compares performance and risk 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 1973 to 31 December 2013 (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 1973 – Dec 2013)	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		Equal Weight	ERC
Ann Returns	10.95%	13.90%	15.67%	15.70%	14.57%	14.96%	15.04%	14.84%
Ann Volatility	17.38%	14.34%	16.69%	16.51%	16.26%	15.95%	15.71%	15.66%
Sharpe Ratio	0.32	0.60	0.62	0.63	0.57	0.61	0.62	0.61
Max DrawDown	54.53%	50.13%	58.11%	58.41%	49.00%	53.91%	53.86%	53.30%
Excess Returns	-	2.95%	4.72%	4.75%	3.62%	4.01%	4.09%	3.88%
Tracking Error	-	6.13%	6.65%	5.74%	4.83%	5.84%	5.15%	4.83%
95% Tracking Error	-	11.53%	11.53%	10.14%	8.58%	10.45%	8.95%	8.07%
Information Ratio	-	0.48	0.71	0.83	0.75	0.69	0.79	0.80

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		Equal Weight	ERC
Ann Returns	7.80%	10.54%	10.45%	10.21%	10.30%	10.37%	10.41%	10.35%
Ann 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

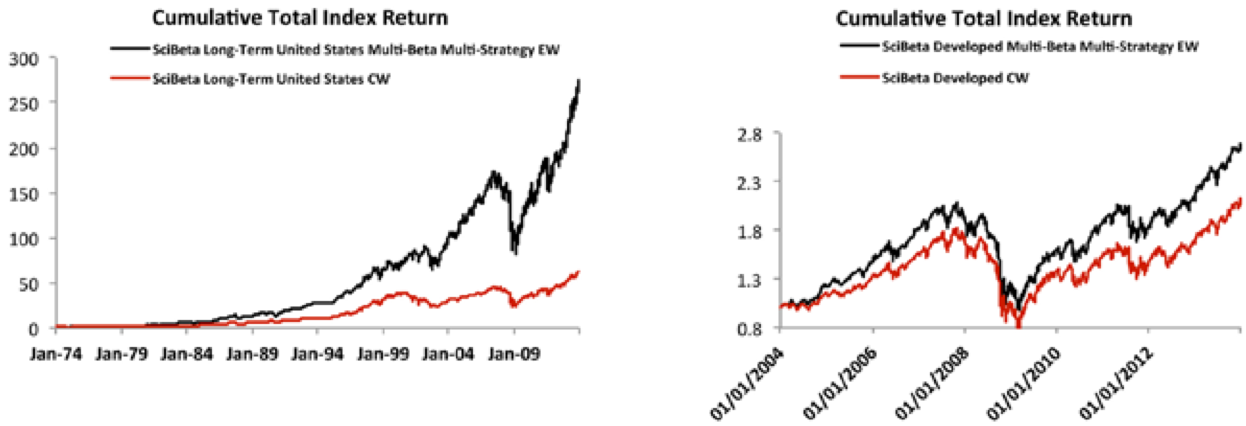
Briefly said, the multi-beta allocations provide the average level of returns of their component indices. However, factor diversification leads to a particularly strong risk reduction (in relative terms), which eventually results in risk-adjusted performance that is well above average. Combining different factors provides a balanced profile: the factor exposures and sector deviations from the cap-weighted sector weights (see Appendix A2) are indeed less extreme for the multi-beta allocations than for the individual constituents.

2. Performance Benefits of Allocating Across Factors

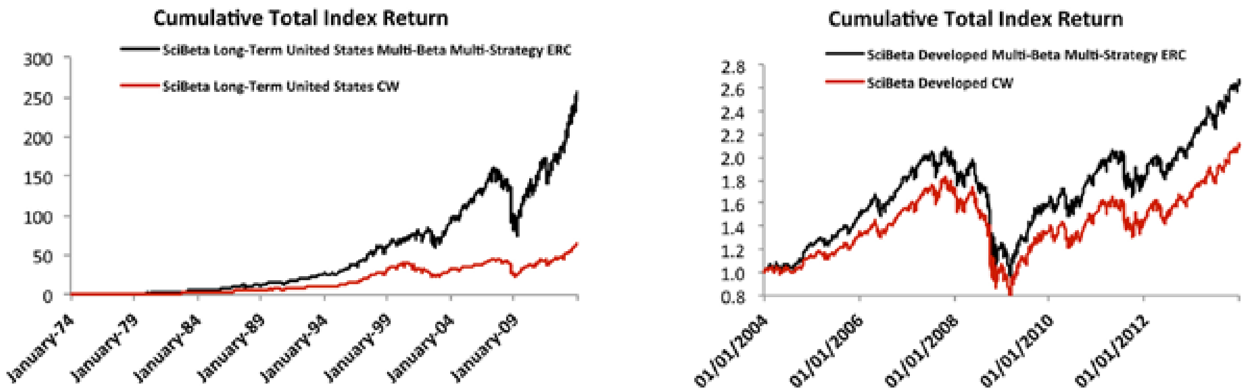
In Exhibit 4, the graphs display the accumulated wealth (i.e. cumulative total index returns) for the SciBeta Multi-Beta Multi-Strategy (MBMS) EW indices (long-term track records and Developed) together with their cap-weighted reference index in the top panel and for the SciBeta MBMS ERC indices (long term track records and Developed) together with their broad cap-weighted index in the bottom panel.

Exhibit 4– Cumulative Index Returns- Exhibit 5 shows the value of a $1 investment in a Multi-Beta Multi-Strategy index and in its cap-weighted reference index. The analysis is based on daily total return data from 31 December 1973 to 31 December 2013 (40 years) using US Long Term data and from 31 December 2003 to 31 December 2013 (10 years) on SciBeta Developed universe.

Panel A – Equal-Weight allocation



Panel B – Equal Risk Contribution allocation



3. Robustness Analysis

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In the context of factor indices and multi-factor indices, two kinds of robustness need to be taken into account – **relative robustness** and **absolute robustness**. A strategy is assumed to be 'relatively robust' if it is able to deliver similar outperformance in similar market conditions. Single-factor indices strive for relative robustness because they aim to deliver good risk adjusted performance for a given factor tilt (e.g. a value factor index would be deemed robust if it aligns well with the value factor performance and does not suffer idiosyncratic losses due to any other causes including, but not limited to, stock specific and sector specific events).

Absolute robustness is the capacity of the strategy to deliver risk-adjusted performance in the future, to a degree that is comparable to that of the past performance, owing to a well-understood economic mechanism rather than by just chance. Absolute robustness is, in other words, the absence of pronounced state and/or time dependencies, and a strategy shown to outperform irrespective of prevailing market conditions can be termed as robust in absolute terms. Absolute robustness can be achieved by allocating across different rewarded risk factors rather than concentrating in a single one.

3.1 Relative Robustness

The relative robustness of underlying single-factor indices is the source of performance of multi-factor indices. If the single-factor indices capture risk premia in an efficient manner, their multi-factor allocation will also provide high risk-adjusted returns. Therefore, in order to improve the relative robustness of multi-factor indices, it is important that constituent single-factor indices be highly robust in relative sense. Relative robustness can be enhanced by the use of a well-diversified weighting scheme that reduces most of the unrewarded risk (stock specific risk and strategy specific risk). The use of the Diversified Multi-Strategy weighting scheme to construct single-factor indices is an attempt to diversify most of unrewarded risk.[5]

Exhibit 5 shows that the extreme risk such as EVT 1% VaR and EVT 1% CVaR of smart beta strategies is less than that of the cap-weighted benchmark. Since Scientific Beta factor and multi-factor indices rely on two levels of diversification – one at stock level and another at strategy level – the concentration in fewer individual stocks or sectors is reduced. The lower level of tail risk of both single-factor Multi-Strategy indices and Multi-Beta Multi-Strategy allocations provides evidence of the said reduction of unrewarded risk and is therefore an indicator of improved relative robustness.

Maximum Relative Drawdown, another important measure of relative robustness, represents the maximum drawdown experienced by an index long in terms of strategy and short in terms of its cap-weighted benchmark. Extreme losses occur in any risky investment and factor indices are not an exception. If the losses cannot be explained by a clear economic rationale, then there are other unintended risks at play which bring down relative robustness of the strategy. The graphs in Exhibit 6 show the wealth ratio of the Scientific Beta Long-Term Track Records and of Scientific Beta Developed Indices (i.e. the ratio of the wealth level of the MBMS index over the wealth level in the

5 - It must be noted that multi-factor allocations do not aim to improve relative robustness of single-factor indices. The relative robustness of multi-factor allocations is dependent on the relative robustness single-factor indices. The objective of combining betas is to improve absolute robustness. This point is illustrated in more detail in Sub-section 3.2.

3. Robustness Analysis

cap-weighted reference). If the wealth ratio goes up it means that the MBMS index is outperforming the cap-weighted index, and the opposite lies true if it goes down.

Exhibit 5 – Extreme Risks and Maximum Relative Drawdown
This table reports absolute and relative extreme risk characteristics of Scientific Beta US Long-Term Track Records (Panel A) and Scientific Beta Developed Indices (Panel B). The analysis is based on daily total return data from 31 December 1973 to 31 December 2013 (40 years) using US Long-Term data and from 31 December 2003 to 31 December 2013 (10 years) on the Scientific Beta Developed universe.

Panel A

US Long-Term Track Records (Dec 1973 – Dec 2013)	USA Long Term Cap Weighted	Scientific Beta Diversified Multi-Strategy					
		Smart Factor Indices				Multi-Beta Allocations	
		Low Vol	Mid Cap	Value	Momentum	EW	ERC
EVT 1% VaR	2.37%	1.90%	2.10%	2.12%	2.15%	2.04%	2.04%
EVT 1% CVaR	2.91%	2.32%	2.55%	2.59%	2.64%	2.49%	2.49%
Ret to EVT 1% VaR ratio	0.15	0.28	0.31	0.30	0.27	0.30	0.29
Ret to EVT 1% CVaR ratio	0.12	0.23	0.25	0.25	0.22	0.24	0.24
For. Monthly EVT 1% VaR	8.56%	7.10%	7.97%	8.41%	8.18%	7.78%	7.74%
For. Monthly EVT 1% CVaR	10.65%	8.73%	9.66%	10.37%	10.06%	9.50%	9.43%
Max Rel DrawDown	-	43.46%	42.06%	32.68%	17.28%	33.65%	28.74%

Panel B

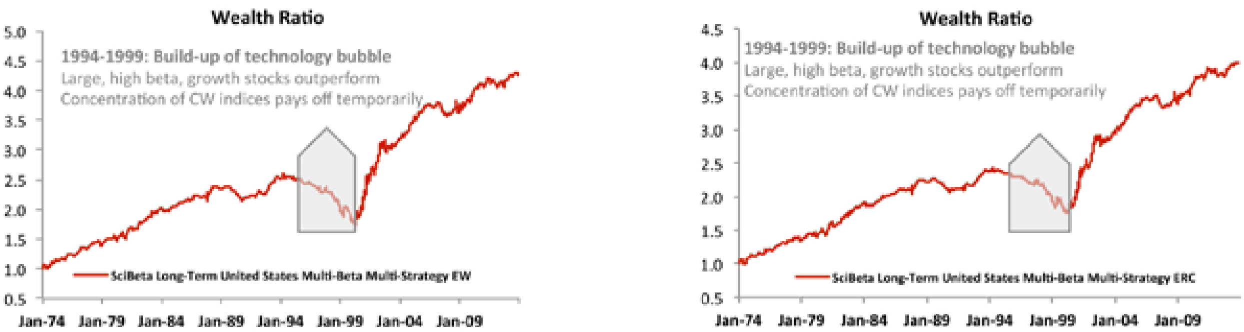
SciBeta Investable Developed Indices (Dec 2003 – Dec 2013)	USA Long Term Cap Weighted	Scientific Beta Diversified Multi-Strategy					
		Smart Factor Indices				Multi-Beta Allocations	
		Low Vol	Mid Cap	Value	Momentum	EW	ERC
EVT 1% VaR	2.08%	1.66%	1.92%	2.08%	1.95%	2.08%	2.08%
EVT 1% CVaR	2.53%	2.01%	2.33%	2.54%	2.38%	2.53%	2.53%
Ret to EVT 1% VaR ratio	0.19	0.34	0.29	0.26	0.28	0.19	0.19
Ret to EVT 1% CVaR ratio	0.15	0.28	0.24	0.21	0.23	0.15	0.15
For. Monthly EVT 1% VaR	7.20%	6.05%	6.50%	7.10%	6.45%	7.20%	7.20%
For. Monthly EVT 1% CVaR	8.93%	7.46%	7.92%	8.75%	7.91%	8.93%	8.93%
Max Rel DrawDown	-	9.20%	6.77%	5.79%	12.00%	6.37%	5.54%

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 – the late 1990s. If you look 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 course, over a short time period, it is possible for this concentration to actually pay 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.

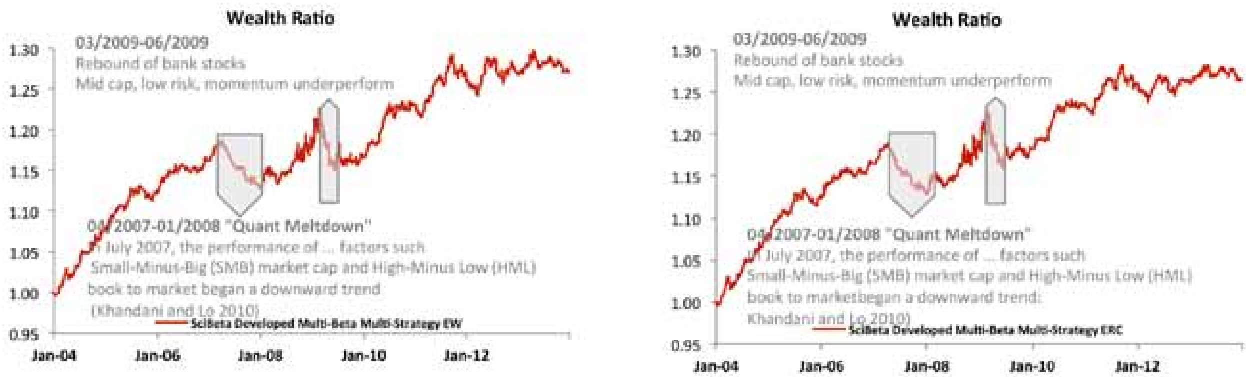
3. Robustness Analysis

Exhibit 6 - Wealth Ratio graphs
Plots display the ratio of the wealth of the Scientific Beta Long-Term Track Records and of the Scientific Beta Developed indices with respect to their cap-weighted benchmark. The analysis is based on daily total return data from 31 December 1973 to 31 December 2013 (40 years) using US Long Term data in Panel A and from 31 December 2003 to 31 December 2013 (10 years) on Scientific Beta Developed universe in Panel B.

Panel A



Panel B



Factor exposure analysis is a particularly important robustness check in the case of single- and multi-factor indices because it discloses what portion of a strategy's performance is indeed derived from its exposure to intended risk factors, and how much can be attributed to other factors and unexplained alpha. Many studies have underlined the importance of factor exposures in explaining part of the outperformance of portfolio strategies over cap-weighted indices (e.g. Jun and Malkiel, 2007; Kaplan, 2008; Blitz and Swinkels, 2008; Amenc, Goltz and Le Sourd, 2008). The analysis provides information on relative robustness by indicating if the strategy is tilted to the intended risk factor(s) ex-post and if the risk and performance of the strategy is explained by the said factor(s).

Exhibit 7 summarises the results of the four-factor model regression analysis of the multi-beta multi-strategy indices and the component single-factor indices. By the nature of their construction, each individual factor-index tends to tilt more towards the corresponding risk factors than the other indices. For example, USA Long-Term Mid Cap Multi-Strategy has SMB beta of 0.31, and USA Long-Term Momentum Multi-Strategy has MOM beta of 0.17. Similarly, the HML beta of USA Long-Term Value

3. Robustness Analysis

Multi-Strategy is 0.31. Meanwhile, for the USA Long-Term Low Volatility Multi-Strategy 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 a small cap factor. Results are similar in nature for Developed universe. Multi-beta multi-strategy indices, however, have a balanced and positive exposure to all rewarded risk factors.

Exhibit 7 – Factor Exposure
The regression coefficients (betas and alphas) statistically significant at 95% level are highlighted in bold. The Market factor is the daily return of cap-weighted index of all stocks that constitute the index portfolio in excess of the risk free rate. Small size factor is the daily return series of a cap-weighted portfolio that is long the smallest 30% of stocks in the broad CW universe by market cap and is short the largest 30% of stocks by market cap. Value factor is the daily return series of a cap-weighted portfolio that is long the highest 30% and is short the lowest 30% of B/M ratio stocks in the broad CW universe. Momentum factor is the daily return series of a cap-weighted portfolio that is long the highest 30% and short the lowest 30% of 52-week (minus most recent 4 weeks) past return stocks in the broad CW universe by market cap. The "Secondary Market US Treasury Bills (3M)" is the risk-free rate in US Dollars. All statistics are annualised. The analysis is based on daily total returns from 31/12/1973 to 31/12/2013 using US Long-Term data and from 31 December 2003 to 31 December 2013 (10 Years) on Scientific Beta Developed universe.

Panel A

US Long-Term Track Records (Dec 1973 – Dec 2013)		USA Long Term Cap Weighted	Scientific Beta Diversified Multi-Strategy					
			Smart Factor Indices				Multi-Beta Allocations	
			Low Vol	Mid Cap	Value	Momentum	EW	ERC
Carhart Regression Betas	Ann Alpha	0.00%	**2.85%**	**2.66%**	**2.33%**	**1.84%**	**2.45%**	**2.35%**
	Mkt Beta	**1.00**	**0.78**	**0.93**	**0.91**	**0.94**	**0.89**	**0.89**
	SMB Beta	0.00	**0.02**	**0.31**	**0.16**	**0.16**	**0.16**	**0.15**
	HML Beta	0.00	**0.14**	**0.16**	**0.31**	**0.09**	**0.17**	**0.16**
	MOM Beta	0.00	0.00	0.00	**0.03**	**0.17**	**0.05**	**0.06**
R-Square		100%	90%	92%	95%	96%	95%	95%

Panel B

SciBeta Investable Developed Indices (Dec 2003 – Dec 2013)		USA Long Term Cap Weighted	Scientific Beta Diversified Multi-Strategy					
			Smart Factor Indices				Multi-Beta Allocations	
			Low Vol	Mid Cap	Value	Momentum	EW	ERC
Carhart Regression Betas	Ann Alpha	0.00%	**3.51%**	**1.58%**	**1.29%**	**1.71%**	**2.03%**	**1.84%**
	Mkt Beta	**1.00**	**0.80**	**0.95**	**0.95**	**0.98**	**0.92**	**0.93**
	SMB Beta	0.00	**0.04**	**0.31**	**0.12**	**0.15**	**0.16**	**0.15**
	HML Beta	0.00	**-0.03**	**-0.05**	**0.17**	**-0.08**	0.00	**0.03**
	MOM Beta	0.00	**-0.01**	**0.05**	**0.06**	**0.21**	**0.08**	**0.08**
R-Square		100%	96%	98%	99%	98%	99%	99%

3.2 Absolute Robustness

In this section, we show how multi-beta allocations improve absolute robustness of single-factor indices, which have already been shown to be highly 'relatively robust' in the previous section.

Since the performance of smart beta varies over time, the analytics reported over long horizons (for example excess returns over 40 years) have limited information due to the effects of averaging over

3. Robustness Analysis

time periods. Probability of outperformance is a measure that overcomes this limitation and hence is a useful tool to measure absolute robustness. The probability of outperformance is defined as the empirical frequency of outperforming the cap-weighted reference index over a given investment horizon. Since smart beta strategies expose the investor to the risk of short-term underperformance relative to the CW benchmark, the frequency of underperformance becomes an important measure when evaluating the consistency of outperformance over time.

The probability of outperformance is calculated using a rolling window of a one-week step size. It is calculated by computing the frequency of obtaining positive excess returns if one invests in the strategy for a period of 1, 3 or 5 years at any point in time. The results in Exhibit 8 and the graphs in Exhibit 9 suggest that the probability of outperformance increases substantially for the multi-beta indices compared to the average across component indices, especially at short horizons. It means that combination of factors indeed improves the chances of outperforming CW benchmark (improves absolute robustness) compared to single factors in isolation.

Exhibit 8 – Probability of Outperformance
The analysis is based on daily total return data from 31 December 1973 to 31 December 2013 (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. Probability of outperformance is the historical empirical probability of outperforming the cap-weighted benchmark over an investment horizon of 1, 3 and 5 years irrespective of the entry point in time. It is computed using a rolling window analysis with window length corresponding to the investment horizon and one-week step size.

Panel A

US Long-Term Track Records (Dec 1973 – 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		Equal Weight	ERC
Outperf Prob (1Y)	-	67.2%	68.1%	70.4%	68.2%	68.5%	74.2%	74.3%
Outperf Prob (3Y)	-	76.4%	74.7%	78.8%	84.5%	78.6%	80.4%	80.6%
Outperf Prob (5Y)	-	85.3%	79.0%	88.3%	91.2%	86.0%	90.3%	90.4%

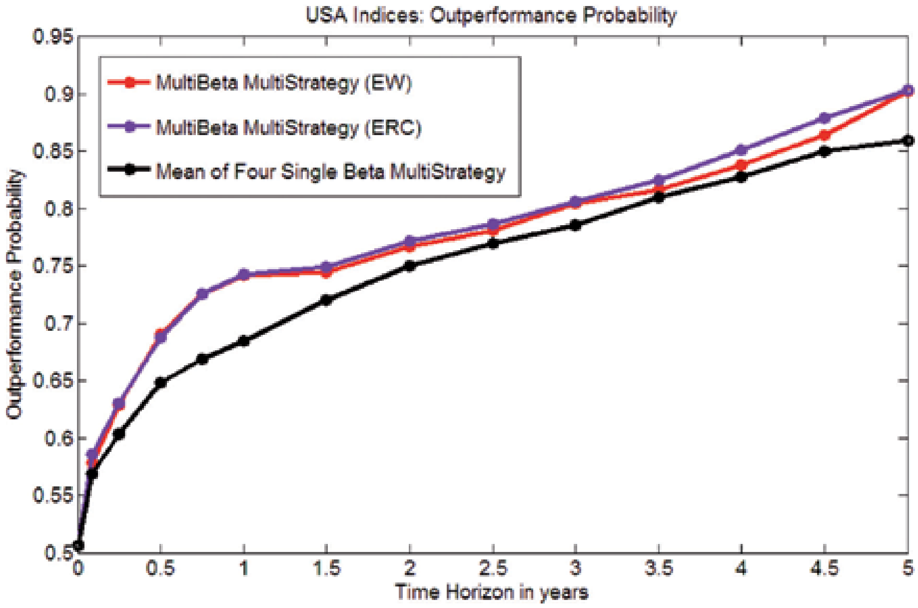
Panel B

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		Equal Weight	ERC
Outperf Prob (1Y)	-	67.7%	78.5%	74.9%	76.0%	74.3%	77.5%	80.6%
Outperf Prob (3Y)	-	93.2%	88.8%	83.1%	79.2%	86.1%	97.5%	100.0%
Outperf Prob (5Y)	-	100.0%	100.0%	95.0%	100.0%	98.8%	100.0%	100.0%

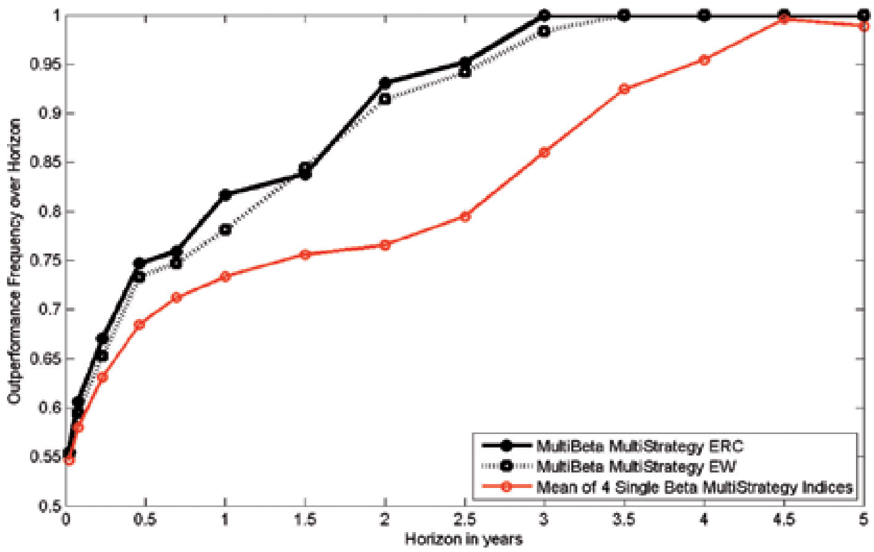
3. Robustness Analysis

Exhibit 9 – Outperformance Frequency of Factor-Tilted Multi-Strategy Indices and Multi-Beta Multi-Strategy Allocations over Different Horizons - The analysis is based on daily total return data from 31 December 1973 to 31 December 2013 (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. Probability of outperformance is the historical empirical probability of outperforming the cap-weighted benchmark over an investment horizon of 1 week, 1 month, 3 months, 6 months, 9 months, 1 year, 18 months, 2 years, 36 months, and so on up to 5 years irrespective of the entry point in time. It is computed using a rolling window analysis with window length corresponding to the investment horizon and a one-week step size.

Panel A - US Long-Term Track Records (Dec 1973 – Dec 2013)



Panel B - SciBeta Investable Developed Indices (Dec 2003 – Dec 2013)



3. Robustness Analysis

Bearing in mind that the rewarded factors yield positive premia in the long term in exchange of 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 NBER definition of business cycles[6] to break down the analysis into alternating sub-periods of 'contraction' and 'expansion' phases. Exhibit 10 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 et al. (2012b) 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. Exhibit 11 shows that the performance of Multi-Strategy factor indices depends on market conditions. For example, the US Long Term Mid Cap Multi-Strategy index post much higher outperformance in bull markets (+5.12%) than in bear markets (+3.83%). The converse is true for the US Long Term Low Volatility Multi-Strategy index which underperforms by 0.99% in bull markets and outperforms by 8.12% in bear markets. If you combine 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 quite impressive in both bull and bear markets. Though, 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. In the end, the multi-beta allocations on the smart factor indices allow premia from multiple sources to be harvested, while resulting in more effective diversification as they achieve a smoother outperformance across the economic cycles and bull/bear market regimes.

6 - 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

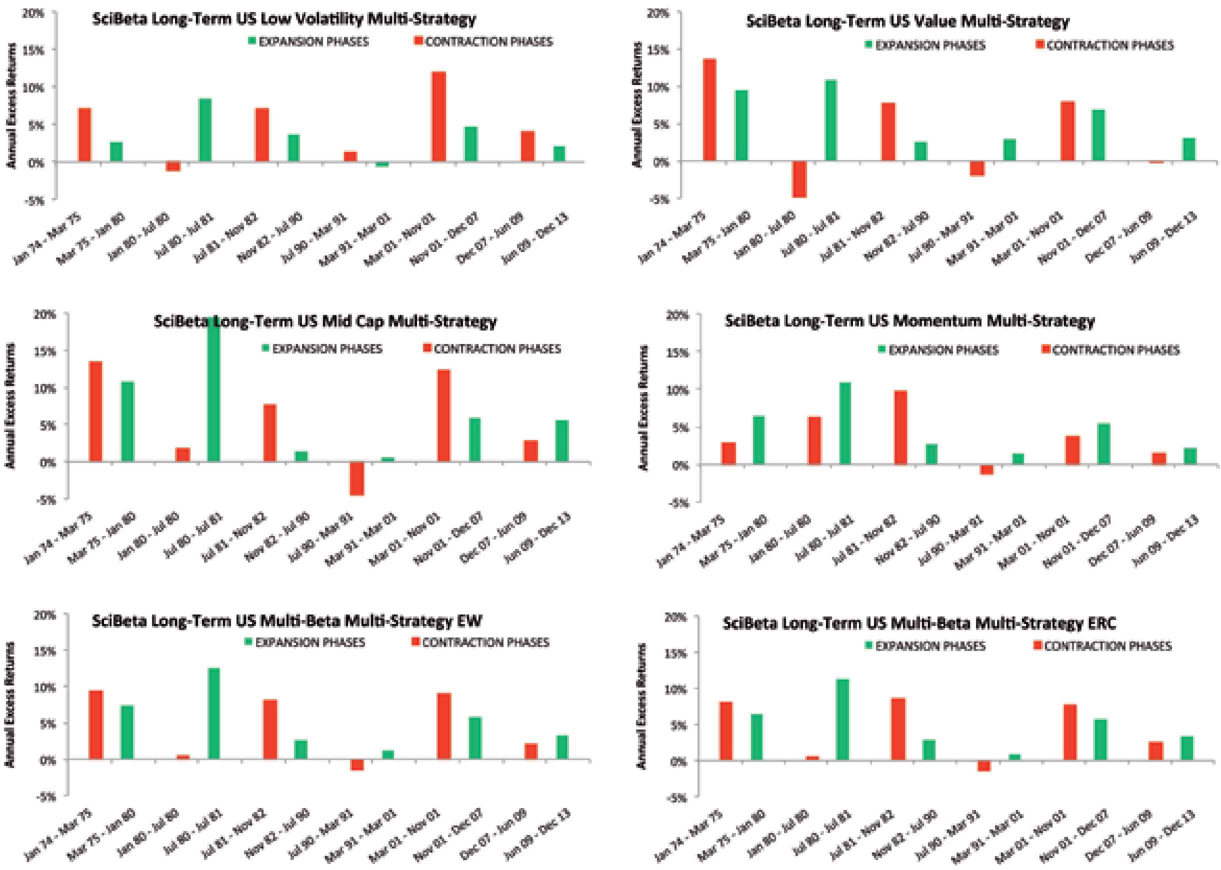
3. Robustness Analysis

Exhibit 10 - Performance of Multi-Beta Multi-Strategy Allocations vs. Single Factor Tilts across Business Cycles - The exhibit shows in Panel A the EW and ERC Multi-Beta allocations overall relative performance contraction and expansion phases of 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 US economy (NBER). 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 31/12/1973 to 31/12/2013 (40 years).

Panel A

US Long-Term Track Records (Dec 1973 – Dec 2013)	Contraction Periods		Expansion Periods	
	EW MBMS	ERC MBMS	EW MBMS	ERC MBMS
Ann. Relative Return	5.19%	4.96%	3.87%	3.67%
Information Ratio	0.75	0.75	0.80	0.82

Panel B



3. Robustness Analysis

Exhibit 11 - Conditional Performance of Multi-Beta Multi-Strategy Allocations and Single Factor Tilts - The exhibit 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 1973 to 31 December 2013 (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 USA (Panel A) and 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 1973 – Dec 2013)	Diversified Multi-Strategy					
	Mid Cap	Momentum	Low Vol	Value	Multi Beta EW Allocation	Multi Beta ERC Allocation
Bull Markets						
Ann Rel Returns	5.12%	3.28%	-0.99%	3.54%	2.79%	2.71%
Ann Tracking Error	5.76%	4.04%	5.11%	5.00%	4.38%	4.13%
Information Ratio	0.89	0.81	-0.19	0.71	0.64	0.66
Bear Markets						
Ann Rel Returns	3.83%	3.77%	8.12%	5.99%	5.49%	5.14%
Ann Tracking Error	8.33%	6.26%	7.94%	7.12%	6.57%	6.12%
Information Ratio	0.46	0.60	1.02	0.84	0.83	0.84

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

4. Implementation Benefits of Allocating Across Factors

4. 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 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. (2014a) 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 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.

Exhibit 12 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 it actually reduces the turnover below the average level observed for component indices. In the table, as opposed to managing the same allocations separately, we provide the amount of turnover that is internally crossed in multi-beta indices for each multi-beta allocation. 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.

4. Implementation Benefits of Allocating Across Factors

Exhibit 12 - 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 1973 to 31 December 2013 (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 US$1bn 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 1973 – 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	34.31%	29.06%	31.54%	38.27%	33.43%	36.84%
Internally Crossed Turnover	-	5.65%	7.52%	-	5.57%	7.67%
Days to Trade for $1 bn Initial Investment (Quantile 95%)(*)	0.20	0.12	0.12	0.16	0.07	0.07
Weighted Avg. Market Cap ($m)	10 039	10 039	10 931	14 229	14 229	16 227
Information Ratio	0.69	0.79	0.80	0.60	0.80	0.82
Relative Returns	4.01%	4.09%	3.88%	3.35%	3.46%	3.07%
Relative Returns net of 20 bps transaction costs (historical worst case)	3.94%	4.03%	3.82%	3.27%	3.39%	2.99%
Relative Returns net of 100 bps transaction costs (extreme liquidity stress scenario)	3.67%	3.80%	3.57%	2.96%	3.13%	2.70%

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 $1 bn Initial Investment (Quantile 95%)	0.48	0.27	0.27	0.20	0.09	0.09
Weighted Avg. Market Cap ($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%

4. Implementation Benefits of Allocating Across Factors

In addition to turnover, the exhibit 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 slightly more than US$ 10bn for the multi-beta index, while the highly liquid version further increases capacity to levels exceeding US$ 16bn 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 US$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.[7] 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 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 3.80%) 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.

7 - 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.

Conclusion - Multi-Smart Beta Allocation: Towards a New Source of Value Added in Investment Management

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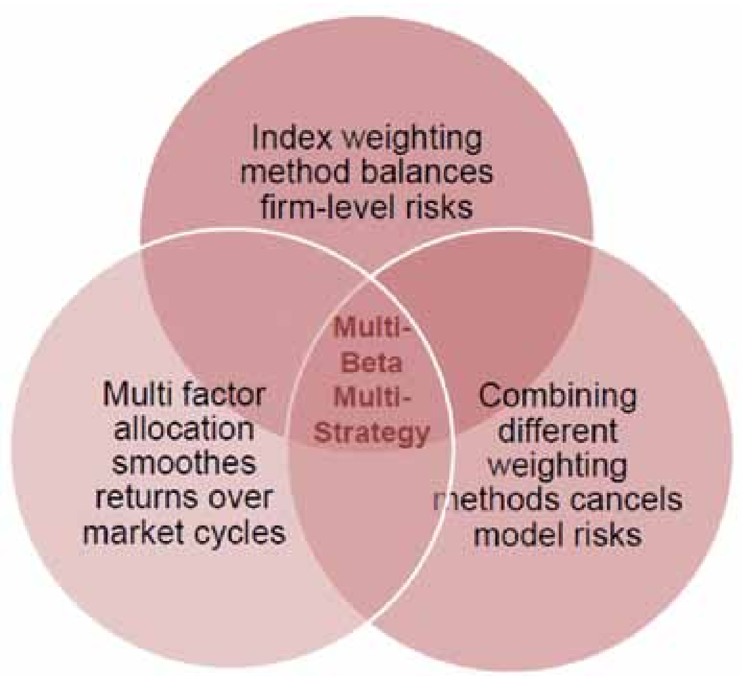
While, in practice, investors may select among various ways of combining smart factor indices in order to account for their investment beliefs, objectives and constraints, the cases of an equal-weighted allocation, and a (relative) equal-risk contribution allocation to four smart factor indices seeking 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 the 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. To this end, ERI Scientific Beta developed the Multi-Beta Multi-Strategy Indices to maximise diversification, benefitting from three levels of diversification: (i) diversify at the stock level to avoid concentration; (ii) diversify the weighting schemes to cancel any remaining model risk; (iii) diversify across sources of returns (factor premia) to obtain smooth outperformance.

Diversification is widely recognised as a major principle of rational investing. In fact, Markowitz (1952), in his seminal work on portfolio construction, states that "a rule of behavior which does not imply the superiority of diversification must be rejected". Scientific Beta's Multi-Beta Multi-Strategy indices draw on this maxim and aim to provide diversification at each step of portfolio construction. This triple diversification leads to a neutral point that avoids taking a bet on the winning stocks, the right weighting scheme, or the best factor tilt.



Appendices

Appendices

Appendix 1 – Groundings of (relative) ERC Allocation

Formally, the risk contribution of an asset to the total risk of a portfolio is given by the weight of the asset in the portfolio times the marginal contribution of the asset to the total portfolio volatility. Qian (2006) shows that decomposing total portfolio volatility in terms of its constituents' risk contributions is more than just a mathematical exercise since it is related to the expected contributions to the portfolio losses, particularly when considering extreme losses.

The Equal Risk Contribution (ERC) portfolio (Maillard et al., 2010) aims to balance the contributions to risk from the different assets in the portfolio. Formally, for all *i*, *j*:

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

where w_i is the (positive) portfolio weight of constituent i and σp 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, so it must be solved numerically. The resulting ERC portfolio can be seen as a middle ground between Minimum Volatility and Equal-Weighted strategies.

Finally, it is straightforward to apply the ERC approach to the excess returns over a cap-weighted reference index, in order to equalise contributions to the tracking-error.

Appendix 2 – Factor and Sector Exposures

The following tables report factor exposures and sector deviations for the multi-beta multi-strategy indices.

The results in Exhibit A.2-1 suggest that – relative to component indices – the multi-beta multi-strategy indices obtain more balanced factor exposure. For example, while the component smart factor indices indices have size exposures ranging from close to zero to about 0.3 (for both US long-term data and Developed indices), the multi-beta indices smooth out these extremes and obtain size exposure in the order of 0.15.

Moreover, when analysing sector deviations with respect to the cap-weighted reference in Exhibit A.2-2, the allocation across smart factor indices with different explicit tilts (i.e. different stock selections) leads to less pronounced sector deviations than those observed for component indices.

Appendices

Exhibit A2-1 - Exposure of Single-Factor Multi-Strategy Factor Indices and Multi-Beta Allocations to Equity Risk Factors
The exhibit shows Carhart 4-factor regression results for Multi-Strategy Factor Indices for four factor tilts – mid cap, high momentum, low volatility, and value – and for EW and ERC allocations on these four factor indices. Factors are based on SciBeta US Long Term Track Records (Panel A) and SciBeta Developed Universe (Panel B). The Market factor is the daily return of the cap-weighted index of all stocks that constitute the index portfolio in excess of the risk-free rate. Small size factor is the daily return series of a cap-weighted portfolio that is long the smallest 30% of stocks (by market cap) and short the largest 30% of stocks (by market cap) of the extended universe (i.e. including small caps). Value factor is the daily return series of a cap-weighted portfolio that is long the 30% highest and short the 30% lowest B/M ratio stocks in the investable universe. Momentum factor is the daily return series of a cap-weighted portfolio that is long the 30% highest and short the 30% lowest 52 weeks (minus most recent 4 weeks) past return stocks in the investable universe. The "Secondary Market US Treasury Bills (3M)" is the risk-free rate in US Dollars. All statistics are annualised. The analysis is based on daily total returns from 31/12/1972 to 31/12/2012 in Panel A and from 31/12/1973 to 31/12/2013 in Panel B. The figures in bold are statistically significant at the 5% level.

Panel A

US Long-Term Track Records (Dec 1973 – Dec 2013)	Diversified Multi-Strategy					
	Mid Cap	Momentum	Low Vol	Value	EW Multi Beta	ERC Multi Beta
Ann Alpha	**2.66%**	**1.84%**	**2.85%**	**2.33%**	**2.45%**	**2.35%**
Market Beta	**0.93**	**0.94**	**0.78**	**0.91**	**0.89**	**0.89**
SMB Beta	**0.31**	**0.16**	**0.02**	**0.16**	**0.16**	**0.15**
HML Beta	**0.16**	**0.09**	**0.14**	**0.31**	**0.17**	**0.16**
MOM Beta	0.00	**0.17**	0.00	**0.03**	**0.05**	**0.06**
R-squared	92.20%	95.52%	90.14%	95.00%	94.76%	95.46%

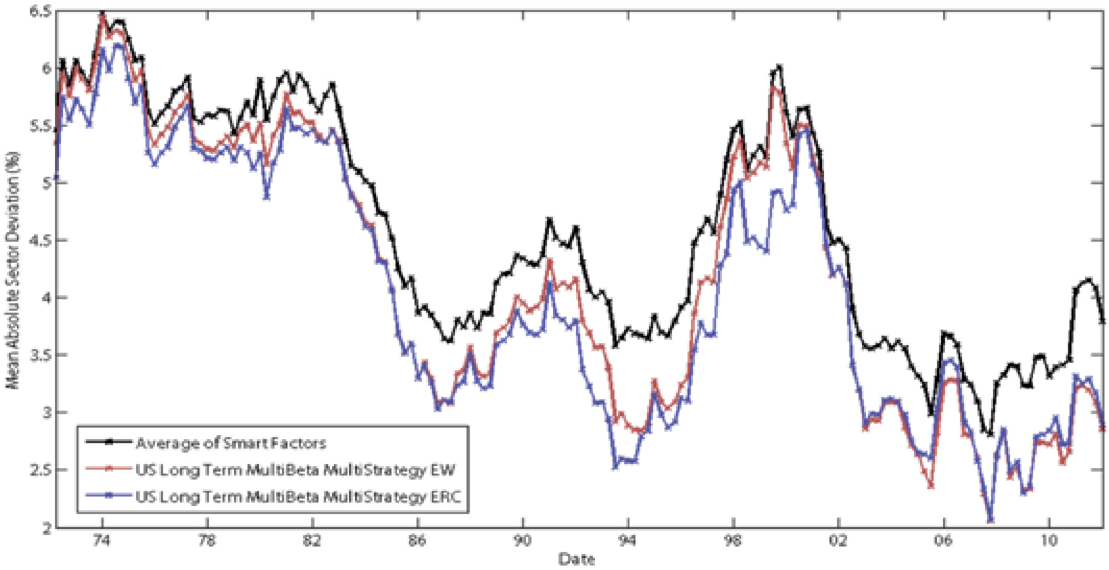
Panel B

SciBeta Investable Developed Indices (Dec 2003 – Dec 2013)	Diversified Multi-Strategy					
	Mid Cap	Momentum	Low Vol	Value	EW Multi Beta	ERC Multi Beta
Ann Alpha	**1.58%**	**1.71%**	**3.51%**	**1.29%**	**2.03%**	**1.84%**
Market Beta	**0.95**	**0.98**	**0.80**	**0.95**	**0.92**	**0.93**
SMB Beta	**0.31**	**0.15**	**0.04**	**0.12**	**0.16**	**0.15**
HML Beta	**-0.05**	**-0.08**	**-0.03**	**0.17**	0.00	**0.03**
MOM Beta	**0.05**	**0.21**	-0.01	**0.06**	**0.08**	**0.08**
R-squared	98.16%	98.39%	96.49%	98.77%	98.81%	98.91%

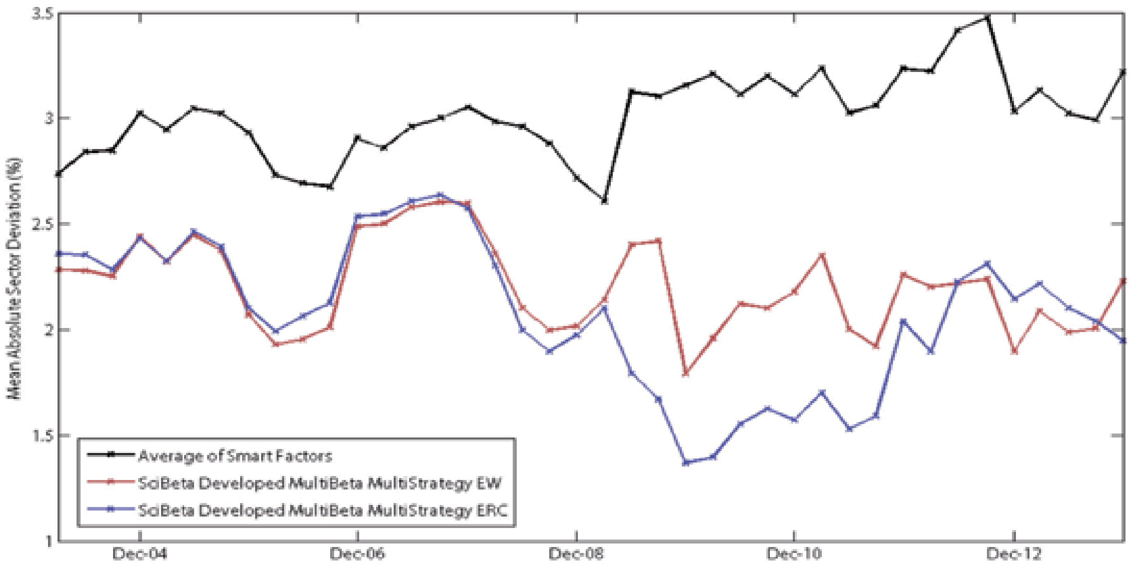
Appendices

Exhibit A2-2 - Mean Absolute Sector Deviation of Multi-Beta Allocations vs. single-beta factor indices
The exhibit shows the mean absolute sector deviation of the multi-beta multi-strategy EW and ERC allocations and the average measure for the single-beta multi-strategy (low volatility, mid-cap, value and momentum) indices. The analysis is based on data from 31/12/1972 to 31/12/2012 in Panel A and from 31/12/2003 to 31/12/2013 in Panel B. The Fama French 12 sic codes sector classification is used in Panel A. The TRBC sector classification is used in Panel B.

Panel A



Panel B



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About ERI Scientific Beta

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• **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.

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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.

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