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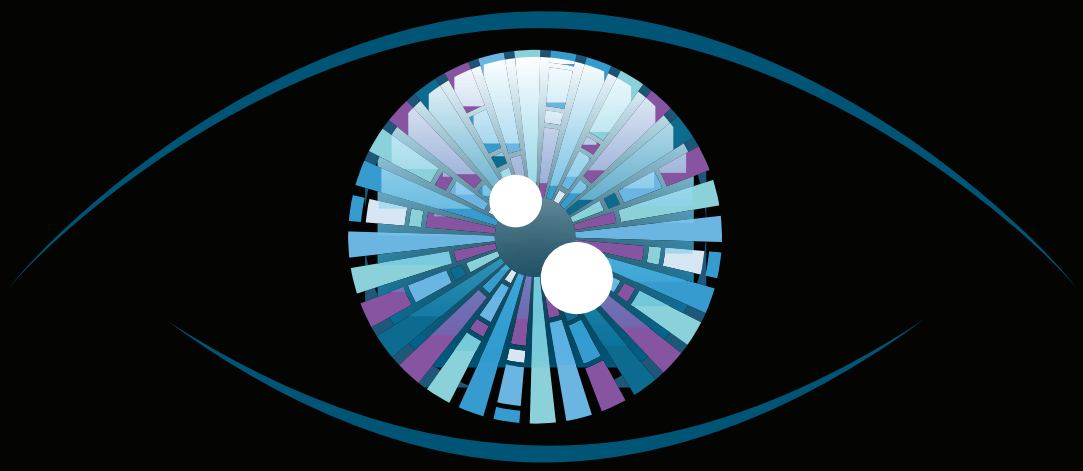

EDHEC Research Insights

The most pressing issues facing investment professionals

AsianInvestor

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Introduction

It is my pleasure to introduce the latest issue of the Research Insights supplement to *AsianInvestor*, which aims to provide institutional investors with an academic research perspective on the most relevant issues in the industry today.

We first show that it is possible to reconcile environmental and financial objectives using low carbon indices. While these indices achieve an environmental objective by excluding high carbon stocks, and thus putting pressure on high polluting companies to reform, they achieve a financial objective by retaining exposure to rewarded risk factors and by maintaining a high level of diversification.

On the subject of defensive solutions and indices, we present three separate articles. We start by looking at the concepts underlying low risk equity strategies and the distinction between exposure to a defensive strategy and benefitting from the reward to the low risk factor. We then introduce alternative approaches to limiting concentration in minimum and low volatility strategies. Finally, we introduce solutions which rely on a risk-based allocation model to dynamically allocate to smart factor indices carrying long-term risk premia, with a view to delivering a dissymmetric defensive profile.

In the final article in the supplement, we look at the live performance of Scientific Beta Multi-Beta Multi-Strategy indices. Live performance does not benefit from hindsight in the way that back-tests potentially can, so the key question for investors is not back-tested performance, but the live performance they will ultimately experience when adopting indices.

We hope that the articles in the supplement will prove useful, informative and insightful. We wish you an enjoyable read and extend our warmest thanks to *AsianInvestor* for their partnership on the supplement.

Noël Amenc
Professor of Finance, EDHEC-Risk Institute, CEO, ERI Scientific Beta

Reconciling environmental and financial objectives with smart beta

By Erik Christiansen, Business Development Manager Europe, ERI Scientific Beta
Kumar Gautam, Senior Quantitative Analyst, ERI Scientific Beta

'The argument is that if investors shift investments to low carbon or green stocks, it would put pressure on polluting firms to reform'

ERI Scientific Beta recently introduced a series of low carbon indices that reduce the carbon footprint of an index using a mild exclusion of high carbon stocks, thereby putting pressure on highly polluting companies to reform, while at the same time retaining exposure to rewarded risk factors and maintaining an appropriate level of diversification. The Scientific Beta Low Carbon Multi-Beta Multi-Strategy indices thus enable both environmental and financial objectives to be reconciled.

Providing a financial incentive for investing in the low carbon economy

For some years now, there has been an increasing interest among investors in low carbon investments. There seem to be two possible reasons for this shift. The first reason, involving a financial consideration, is investors' belief that exposing portfolios to securities with a low carbon footprint would be profitable in the long term, as it would avoid regulatory risk associated with high carbon stocks and would mean investing in green stocks which would profit from the transition to a low carbon economy. The second reason, involving a non-financial consideration, is investors' belief in contributing towards the transition to a low carbon economy. The argument is that if investors shift investments to low carbon or green stocks, it would put pressure on polluting firms to reform.

Unfortunately, a thorough analysis of the way financial markets operate and of the pricing of financial assets would suggest that higher profitability of green stocks vis-à-vis the rest is not certain.

In the academic literature there is broadly a consensus about non-financial considerations involved in Socially Responsible Investing (SRI), which also includes low carbon investments, and the possibility of change in a firm's behaviour through a shift in investments away from securities of high carbon emitting companies. For example, Heinkel et al. (2001) show that in an equilibrium setting, if "green investors" shun polluting companies, there would be a downward pressure on the share price, and "non-green investors" would demand higher expected returns to hold shares of such companies, thus raising the cost of capital for the polluting firms, and thus incentivising them to reform.

On the other hand, when it comes to purely financial considerations, there is evidence in the academic literature that questions the profitability of low carbon investments.

First of all, the argument about profitability of low carbon investments does not fit well into financial asset pricing theory. 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 risk factors with multiple prices. 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). A potential future climate crisis is a good illustration of such a "bad time." Because they could serve as a

'Investors would want, if and when climate change-related distress occurs, to be invested in those companies likely to benefit'

hedge by providing income during bad times, investors could actually be willing to pay a premium for holding low carbon stocks: investors would want, if and when climate change-related distress occurs, to be invested in those companies likely to benefit, or at least to lose less, in such an economic context. If one makes the assumption that companies that currently have lower carbon emissions than their peers would be among those sought-after companies in future distressed times (in the future, for instance, governments might want to "punish" – through taxation, fines, regulations or otherwise – those companies deemed responsible for the dire times, much as banks have been burdened by governments in the aftermath of the recent financial crisis), an investor should be willing to pay a premium for companies which currently have lower carbon emissions.

From an empirical perspective, a large part of the academic literature establishes that there are no or insignificant benefits from low carbon investing as compared to conventional investing, from a financial point of view. For example, Ibikunle and Steffen (2015) focus particularly on green funds and compare their performance to "black" (i.e. fossil energy and natural resources) and conventional European mutual funds for the period 1991-2014. During this sample period, the green mutual funds exhibited lower returns than black and conventional mutual funds. The green mutual funds also had higher volatility than the conventional mutual funds, which can be attributed to lower diversification potential due to restricted investment universes.

In the same vein as this empirical literature, we compare the historical profitability of low and high carbon stocks. To do so, we create a portfolio of 25% Worst-in-Class carbon intensity stocks and another portfolio of 25% Best-in-Class carbon intensity stocks in the Scientific Beta Developed universe. We analyse their performance from 31 December 2005 to 31 December 2015. In Exhibit 1 below, we note that during this 10-year period, the annualised return of the Low Carbon Factor is 1.15%, but a high p-value of 0.28 suggests that we

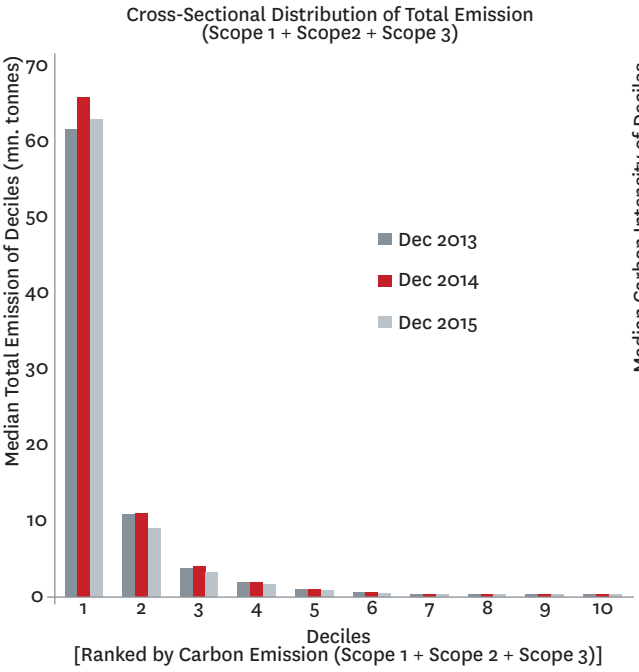
Exhibit 1: Performance of Low Carbon Factor

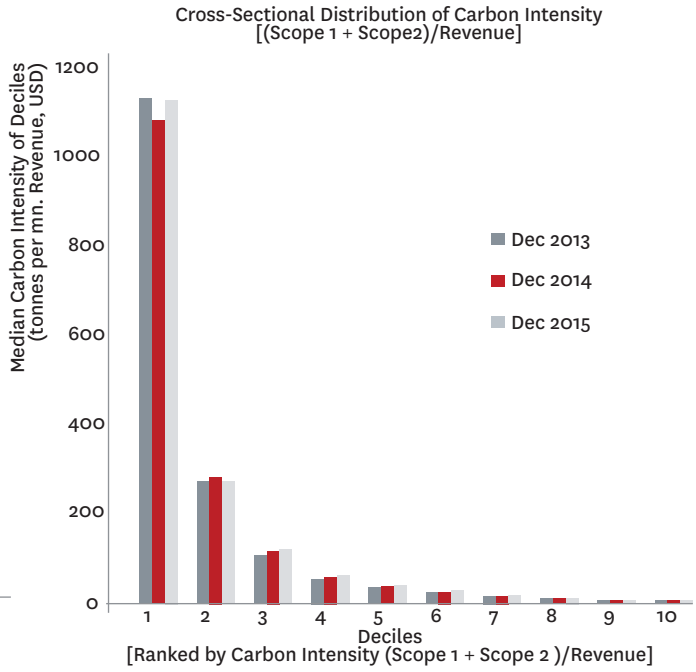
The time period of analysis is December 31, 2005 to December 31, 2015 (10 years). To report performance, we use daily total return series in US dollars. The 25 % Best- (or Worst-) in-Class Intensity Stocks consists of the top (or bottom) 25% carbon intensity stocks from each Level 2 sector of TRBC industry classification, wherein intensity is measured as the ratio of the sum of Scope 1 and Scope 2 emission to the company's revenue. In case any one of the Level 2 sectors does not have at least four stocks, we exclude stocks at the Level 1 sector of TRBC industry classification. The Scope 1 emission refers to Greenhouse Gas (GHG) emission from sources that are owned and/or controlled by the company. The Scope 2 emission refers to indirect GHG emission from generation of electricity, steam or heat purchased/consumed by the company. The source of a company's emission data is South Pole. We use a company's carbon emission data for the year t only starting December rebalancing of year t+1. For years prior to 2011, we make an assumption that a company's carbon emissions were the same as in 2011. The Low Carbon Factor is created as the difference in daily return of 25% Best-in-Class and 25% Worst-in-Class intensity stocks. The portfolios are cap-weighted. *Reports p-value for the null hypothesis that the mean return is zero.

	SciBeta Developed Cap-Weighted	25% Best-in-Class Intensity Stocks (Cap-Weight)	25% Worst-in-Class Intensity Stocks (Cap-Weight)	Low Carbon Factor
Annualised Return (31/12/2005 / 31/12/2015)	5.58%	6.53%	5.43%	1.15% [0.28]*
		Yearly Performance		
2006	20.53%	17.23%	20.94%	-3.06%
2007	11.41%	15.78%	10.11%	5.19%
2008	-40.40%	-44.21%	-38.82%	-8.31%
2009	30.52%	32.04%	30.48%	1.34%
2010	12.64%	17.87%	11.54%	5.73%
2011	-5.59%	-3.79%	-6.34%	2.89%
2012	16.43%	18.56%	15.29%	2.92%
2013	26.81%	27.12%	27.43%	-0.24%
2014	5.09%	6.84%	7.10%	-0.23%
2015	0.02%	3.37%	-2.69%	6.27%

Exhibit 2: Cross-Sectional Distribution of Total Emission and Carbon Intensity

The exhibit plots cross-sectional distribution of Total Emission and Carbon Intensity of stocks in the Scientific Beta Developed universe of 2,000 stocks at the last three December rebalancings. We rank stocks by their total emission (and carbon intensity) and report the median total emission (and carbon intensity) of each decile. Total Emission is defined as the sum of Scope 1, Scope 2 and Scope 3 emissions. Carbon intensity is defined as the ratio of the sum of Scope 1 and Scope 2 emission to the company's revenue. The Scope 1 emission refers to Greenhouse Gas (GHG) emission from sources that are owned and/or controlled by the company. The Scope 2 emission refers to indirect GHG emission from generation of electricity, steam or heat purchased/consumed by the company. The Scope 3 emission refers to GHG Emissions that are a consequence of the activities of the company, but occur from sources not owned or controlled by the company. The source of a company's emission data is South Pole.





cannot reject the hypothesis that there is no premium, at a reasonable significance level.

One can also argue that the financial markets do not yet incorporate the consequences of global warming. In that case, selecting securities of companies with low greenhouse gas emissions would be a "free option" or serve as cheap protection from the negative economic consequences of climate change. That said, however, the success of this approach assumes that the players in the financial sector will be able to identify the companies that do not have their environmental properties correctly priced into the current market value of their securities. However, this assumption runs contrary to findings of academic studies, which demonstrate the inability of asset managers to persistently outperform the market through stock picking.

These findings lead us to the conclusion that if we truly want the finance industry to contribute to saving the planet, we have to encourage it to do so, and not solely rely on the potential profitability of green stocks. Our research shows that it is possible to reconcile environmental and financial objectives using low carbon indices introduced by ERI Scientific Beta, which aim to outperform the market not because they are green, but because they are exposed to traditional risk premia and are better diversified than traditional cap-weighted indices.

Exhibit 3: Smart Beta 2.0 Approach

'Total emissions and carbon intensity are highly concentrated in a few stocks'

How does one reduce carbon emissions, while providing exposure to consensual risk premia and remaining well diversified?

A first question that comes to mind when designing a low carbon index is how much of the universe needs to be impacted in order to achieve a meaningful reduction in carbon emissions? To answer this question, we look at the cross-sectional distribution of both the total emissions and the carbon intensity of stocks. We observe that both factors are highly concentrated in a few stocks. Thus, to achieve a significant reduction in the carbon emissions of the index, it is not necessary to remove a large number of companies, which could also possibly alter the performance and risk characteristics of the index.

Based on these findings, ERI Scientific Beta designs a low carbon index which mildly excludes high carbon stocks and uses techniques to construct an index which is well exposed to the rewarded factors and is well diversified.

ERI Scientific Beta's approach to excluding high carbon stocks relies on excluding stocks that are identified by any of the following criteria, applied independently: coal mining companies[1], top 2% companies by Total Emission in

Exhibit 4: Performance Analysis

The time period for analysis is December 31, 2005 to December 31, 2015 (10 years). We use daily Total Return series in USD. We use SciBeta Developed Cap-Weighted index as the benchmark for relative analysis.

Panel 1	Standard Indices (Developed)								
	CW	Diversified Multi-Strategy						Multi-Beta Multi-Strategy EW	
		Mid Cap	Value	High Mom.	Low Vol.	High Prof.	Low Inv.	Four-Factor	Six Factor
Absolute Performance									
Ann. Ret.	5.58%	7.53%	6.37%	7.19%	8.58%	9.03%	8.30%	7.46%	7.86%
Ann. Vol.	17.34%	16.26%	17.43%	16.25%	13.98%	15.64%	15.57%	15.85%	15.74%
Sharpe Ratio	0.26	0.39	0.30	0.37	0.53	0.51	0.46	0.40	0.43
Relative Performance (w.r.t. CW)									
Ann. Rel. Ret.	-	1.96%	0.80%	1.61%	3.01%	3.46%	2.72%	1.88%	2.29%
Tracking Error	-	3.29%	2.24%	3.69%	4.43%	3.19%	2.99%	2.60%	2.61%
Information Ratio	-	0.59	0.36	0.44	0.68	1.08	0.91	0.72	0.88

Panel 2	Low Carbon Indices (Developed)								
	CW	Diversified Multi-Strategy						Multi-Beta Multi-Strategy EW	
		Mid Cap	Value	High Mom.	Low Vol.	High Prof.	Low Inv.	Four-Factor	Six Factor
Absolute Performance									
Ann. Ret.	5.58%	7.68%	6.33%	7.57%	8.85%	9.33%	8.22%	7.64%	8.02%
Ann. Vol.	17.34%	16.36%	17.19%	16.04%	13.76%	15.48%	15.45%	15.70%	15.59%
Sharpe Ratio	0.26	0.40	0.30	0.40	0.56	0.53	0.46	0.42	0.44
Relative Performance (w.r.t. CW)									
Ann. Rel. Ret.	-	2.11%	0.75%	1.99%	3.27%	3.75%	2.65%	2.06%	2.45%
Tracking Error	-	3.42%	2.33%	3.81%	4.69%	3.44%	3.26%	2.78%	2.82%
Information Ratio	-	0.62	0.32	0.52	0.70	1.09	0.81	0.74	0.87
Low Carbon vs. Standard Indices									
Diff. in Annual Return	-	0.15%	-0.05%	0.38%	0.26%	0.29%	-0.07%	0.18%	0.16%
Tracking Error	-	0.96%	1.22%	1.12%	1.08%	0.96%	1.11%	0.80%	0.77%

[1] We identify coal mining companies as companies with Thomson Reuters Business Classification (TRBC) code of 501010.

Exhibit 5: Difference in Risk Factor Exposures

The time period for analysis is from 31 December 2005 to 31 December 2015 (10 years). We report absolute differences in betas from Risk Factor Exposure (seven-factor) analysis of Scientific Beta standard indices and the corresponding low carbon indices. The market factor is cap-weighted and is created as the difference in return of SciBeta Developed Cap-weighted and risk-free rate (return of the Secondary Market US Treasury Bills (3M)). The other six factors are the long/short equal weight factors from Scientific Beta (www.scientificbeta.com).

	Difference in Betas: Low Carbon Indices vs. Corresponding Standard Indices (Developed)								
	Diversified Multi-Strategy						Multi-Beta Multi-Strategy EW		
	Mid Cap	Value	High Mom.	Low Vol.	High Prof.	Low Inv.	Four-Factor	Six Factor	Average across indices
Market Beta	0.00	0.00	0.01	0.01	0.01	0.00	0.00	0.00	0.00
SMB Beta	0.01	0.03	0.00	0.01	0.00	0.01	0.02	0.01	0.01
HML Beta	0.00	0.00	0.03	0.01	0.05	0.00	0.01	0.02	0.02
MOM Beta	0.01	0.00	0.02	0.02	0.00	0.01	0.00	0.00	0.01
VOL Beta	0.02	0.00	0.01	0.02	0.01	0.00	0.01	0.01	0.01
PRO Beta	0.04	0.02	0.01	0.01	0.03	0.01	0.02	0.01	0.02
INV Beta	0.03	0.02	0.08	0.05	0.04	0.00	0.05	0.04	0.04
Average Across Exposures	0.02	0.01	0.02	0.02	0.02	0.01	0.02	0.01	0.02

Exhibit 6: Carbon Metrics

The exhibit reports carbon metrics and change in carbon metrics of Scientific Beta low carbon indices compared to the cap-weighted benchmark as of 18 December 2015. The Carbon Metrics report two measures: the Carbon Footprint and the Carbon Intensity. The Carbon Footprint of the index represents the total emissions in relation to an investment of US$1 billion in the index. The Carbon Intensity of the index is the weighted average carbon intensity of the individual companies in the index. The units for carbon footprint and carbon intensity are tonnes per billion investment in dollars and tonnes per million revenue in dollars, respectively. A negative (positive) change in carbon metrics implies a reduction (increase) in carbon metrics with respect to the broad cap-weighted benchmark.

		Low Carbon Indices (Developed)							
	CW	Diversified Multi-Strategy						Multi-Beta Multi-Strategy EW	
		Mid Cap	Value	High Mom.	Low Vol.	High Prof.	Low Inv.	Four-Factor	Six Factor
					Carbon Metrics				
Carbon Footprint	642,126	362,584	535,571	238,776	277,185	195,381	427,990	353,529	339,581
Carbon Intensity	183	112	166	69	130	48	131	119	109
					Change in Carbon Metrics (w.r.t. Cap-Weighted Index)				
Carbon Footprint	-	-45.53%	-16.59%	-62.81%	-56.83%	-69.57%	-33.35%	-44.94%	-47.12%
Carbon Intensity	-	-38.54%	-9.17%	-62.09%	-29.05%	-73.67%	-28.16%	-34.71%	-40.11%

the broad Developed universe, top 2% companies by Total Emission in each of Scientific Beta's geographic basic blocks and top 25% companies by Carbon Intensity in each of the level 2 sub-sector (or level 1 sector in case any one of the level 2 sub-sectors does not have at least four stocks).

Once we exclude stocks based on carbon emissions, we apply ERI Scientific Beta's approach termed Smart Beta 2.0. The approach distinguishes two steps in the construction of smart beta strategies, with the first step tilting towards the targeted risks by way of transparent security selection, and the second step diversifying away the undesired and unrewarded risks through the application of a diversification strategy (smart weighting scheme). Smart factor indices are thus tilted towards the desired risk factors but also well diversified.

ERI Scientific Beta's multi-smart factor indices are constructed using smart factor indices, representing a set of six academically-documented and popular risk factors – Size, Momentum, Volatility, Valuation, Investment and Profitability.

Scientific Beta Low Carbon Indices: better financial performance, lower carbon emissions

We first analyse the financial performance of Scientific Beta Low Carbon Indices and compare it with the standard (without any low carbon filter) Scientific Beta indices. In Exhibit 4 we report performance of standard (Panel 1) and low carbon (Panel 2) indices for the Developed market for the 10-year period from 31 December 2005 to 31 December 2015. We note that both standard and low carbon Scientific Beta indices covered here outperform the cap-weighted benchmark. Moreover, the performance of low carbon indices is very similar to that of the standard indices.

Next we report the absolute difference in risk factor exposures between the standard and low carbon indices. The average difference in exposure across all risk factors is as low as 0.02, which means the Scientific Beta methodology to construct low carbon indices does not significantly change their exposure to financially rewarded factors. This also suggests that the likelihood of significant differences in their performance over the long term is low.

We then analyse the impact on carbon metrics, with two measures: the carbon footprint and the carbon intensity. In Exhibit 6, we report these metrics for the low carbon indices. To give perspective, we also show the change in these measures with respect to the broad cap-weighted index. We note that for the low carbon SciBeta Developed Multi-Beta Multi-Strategy indices, the reduction in carbon footprint is close to 45%.

Conclusion

Our results show that it is possible to reconcile environmental and financial objectives using low carbon indices introduced by ERI Scientific Beta. While on the one hand these indices achieve an environmental objective by excluding high carbon stocks, and thus putting pressure on high polluting companies to reform, on the other, these indices achieve a financial objective by retaining exposure to rewarded risk factors and by maintaining a high level of diversification. Compared to the corresponding cap-weighted index, the Scientific Beta Developed Multi-Beta Multi-Strategy EW Six Factor Index reduces both the carbon footprint and the carbon intensity by more than 40%, while generating an excess return of 2.45% over the cap-weighted index.

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Distinction between exposure to a defensive strategy and benefitting from the reward to the Low Risk Factor

By Noël Amenc, Professor of Finance, EDHEC-Risk Institute, CEO, ERI Scientific Beta; Frédéric Ducoulombier, Head of Business Development for Asia ex Japan, ERI Scientific Beta, Associate Professor of Finance, EDHEC Business School; Ashish Lodh, Deputy Research Director, ERI Scientific Beta

Introduction

In the context of defensive investing, investors often confuse being exposed to a defensive strategy, such as Efficient Minimum Volatility, and benefitting from the reward to the Low Risk Factor. The reason being the two types of defensive strategies, i.e. Low Volatility and Minimum Volatility, which derive from different academic traditions, i.e. factor investing and modern portfolio theory, respectively, can produce comparable levels of risk reduction in practice. While factor-investing strategies aiming to extract the Low Risk factor premium were introduced in a long/short setting and as such could be market neutral, their long-only unleveraged implementations, i.e. Low Volatility/Beta strategies, naturally acquire a defensive character as they overweight low risk stocks.

Modern Portfolio Theory Minimum Volatility strategies, on the other hand, are intended to be defensive, as they explicitly aim to identify the portfolio with the lowest risk on Markowitz's (1952) efficient frontier. While they give no consideration to factor exposures and explicitly rely on exploiting both low individual stock volatilities and low pair-wise correlations between stocks, traditional implementations of Minimum Volatility investing can be expected to produce portfolios that are dominated by low risk stocks and, as such, could indirectly produce significant exposure to the Low Risk factor (assuming sufficient diversification of idiosyncratic risk). ERI Scientific Beta makes a clear distinction between these two approaches, which, even though they have points in common (low beta, exposure to low volatility risk), do not have the same objectives or the same long-term performance and risk.

The Low Risk Factor

The Low Risk factor occupies a particular place in the asset pricing literature as the performance of low risk strategies appears to directly contradict the central prediction of the CAPM, i.e. that returns should be linearly related to systematic market risk (as measured by market beta, i.e. the covariance between the returns of the portfolio and those of the market standardised by the variance of market returns). Below we underline that the said performance is one of the strongest results in empirical finance, that it has spurred a rich literature on the rewarded factors in asset prices and that it is supported by theoretical justifications.

The lack of empirical success for the CAPM, the founding model of asset pricing theory, prompted a search for better asset pricing models which led to theoretical advances starting with Black's (1972) restricted borrowing CAPM and, following the proposal of multi-factor models with Merton's (1973) inter-temporal CAPM and Ross' (1976) arbitrage theory of capital asset pricing, to the search for and identification of priced factors in equity returns beyond market risk, the single factor posited by the CAPM, and from Fama and French (1992, 1993) onwards to their inclusion in multi-factor pricing models.

While the low risk "anomaly" first documented by Friend and Blume (1970), Black, Jensen, and Scholes (1972), Miller and Scholes (1972) and Haugen and

'The performance of low risk strategies appears to directly contradict the central prediction of the CAPM'

Heins (1972, 1975), was responsible for triggering the work that led to these theoretical and empirical advances in multi-factor asset pricing, the "anomaly" has survived to this day[2] and has been rejuvenated by recent theoretical work. Influential work by Ang, Hodrick, Xing and Zhang (2006, 2009) finds that stocks with high total volatility underperform and that stocks with high recent idiosyncratic volatility have low average returns that are not explained by the size, book-to-market and momentum effects of Fama and French (1992, 1993) and Jegadeesh and Titman (1993). While a number of papers try to explain the idiosyncratic volatility results of Ang et al. away (see Martellini, 2013 for a review), others, such as Chen, Jiang, Xu and Yao (2012) defend it as a common phenomenon. Stambaugh, Yu and Yuan (2015) justify the negative relation between idiosyncratic volatility and average return by restrictions on short sales that limit the shorting of overpriced stocks (which they contend exhibit the negative relationship, particularly in periods of high investor sentiment).[3] Complementing behavioural explanations of the performance of defensive strategies, Baker, Bradley and Wurgler (2011) note that tracking error constraints in benchmarked institutional management discourage arbitrage activity in both high-alpha low-beta stocks and low-alpha high-beta stocks.

Following on from Black (1972, 1993), Frazzini and Pedersen (2014) present a model of leverage-constrained investment that explains why investors seeking a high degree of market risk[4] cause low-beta assets to overperform high-beta assets on a risk-adjusted basis. They document that the "betting against beta" strategy, which is long leveraged low-beta assets and short high-beta assets, produces significant positive risk-adjusted returns. Importantly, they show that the poor returns of the strategy when funding constraints become tight are consistent with liquidity-constrained investors having to sell leveraged positions in low-risk assets in bad times, providing a risk-based justification for the observed premium.

Nature and limits of defensive strategies

The implementation of Low Risk factor harvesting in a long-only and zero-leverage environment creates a defensive risk/return profile as a by-product, while the practical implementation of defensive Minimum-Volatility strategies will typically lead to portfolios dominated by low volatility stocks, which could potentially reap some of the benefits of the Low Risk factor as a side effect. Note that the confusion between Minimum Volatility strategies deriving from Modern Portfolio Theory and Low Volatility factor strategies owes a lot to MSCI, which has been marketing its Minimum Volatility indices as Low Volatility Factor indices. Below we discuss separately the properties and limitations of the two kinds of defensive strategies.

Minimum volatility strategies

In the Markowitz framework, the Global Minimum Variance portfolio is a remarkable portfolio that lies on the efficient frontier and provides the lowest possible portfolio volatility. Identifying this portfolio requires the variance-covariance matrix as an optimisation input. From a theoretical standpoint and as explained by Tobin (1958), minimum variance portfolios are not optimal in the presence of a riskless asset since they are dominated by a combination of the optimal risky portfolio maximising the risk/return trade-off (tangency portfolio) and the riskless asset. In this context, the minimum variance portfolio coincides with the optimal risky portfolio only when the expected returns of all assets are identical, a rather unrealistic optimality condition.

In practice however, identifying the tangency portfolio in the traditional manner is extremely difficult as it requires estimation of the expected returns for use in optimisation. Indeed, as shown by Merton (1980), a long history is required to estimate an expected return that is known to be constant, and there is no reason why such an expected return should be a constant. The higher degree of estimation error associated with estimating the tangency portfolio in the traditional way could more than offset the benefits of an absence of optimality risk. For illustration, Jorion (1985) or Jagannathan and Ma (2003) find that tangency portfolios do not perform as well as the global minimum variance portfolios when assessed in terms of out-of-sample Sharpe Ratio.

However, even though the Global Minimum Variance portfolio is easier to estimate, there are nonetheless challenges in constructing this type of portfolio. Unconstrained minimum variance optimisation typically produces portfolios that are extremely concentrated (in a small number of low volatility stocks) and suffer from severe sector biases (Chan, Karceski, Lakonishok, 1999). Furthermore, as

[2] Black (1993) contends that this evidence is stronger than the corresponding evidence for the factors introduced by Fama and French (1992, 1993). Empirical studies documenting the performance of low risk portfolios also include Haugen and Baker (1991); Jangannathan and Ma (2003); Fama and French (2004); Clarke, de Silva and Thorley (2006) and Baker, Bradley, and Wurgler (2011). While the aforementioned studies concern U.S. markets, the same effect has been documented for global equity markets by Blitz and van Vliet (2007), Baker, Nardin and Haugen (2012) and Baker, Bradley, Taliaferro (2014), among others.

[3] Hong and Sraer (2015) show how, in the presence of short-sale restrictions, disagreement amongst investors on the future cash flows of firms leads to overpricing of stocks. As disagreement increases with a stock's beta, high beta stocks, which are more sensitive to aggregate disagreement than low beta ones, are only held in equilibrium by optimists as pessimists are sidelined. This greater divergence of opinion creates relative overpricing of high beta stocks. Analyst over-optimism regarding high-growth high-volatile stocks and insufficient discernment on the part of investors reacting to these forecasts has been put forward as a behavioural explanation of the Low Volatility effect by Hsu, Kudoh, and Yamada (2013).

[4] Note that this is different from an irrational preference for highly volatile "lottery stocks" and "glamour stocks" that has been offered as a behavioural explanation for the Low Risk phenomenon.

'The seminal empirical and theoretical literature on factor investing underlines the importance of diversification'

optimised concentrated portfolios, they should be expected to exhibit very high turnover if parameters are time-varying and they do (e.g. Clarke, de Silva and Thorley, 2011).

As for documentation of the concentration of minimum volatility portfolios, Clarke, de Silva and Thorley (2011) observe that their long-only minimum variance portfolio is constituted on average of 12% of their 1,000-security universe while DeMiguel et al. (2009) note that "short-sale-constrained minimum-variance portfolios (...) tend to assign a weight different from zero to only a few of the assets." These difficulties often result therefore in unconstrained minimum volatility-type portfolios being concentrated and poorly diversified over a small number of low-volatility stocks. In order to remedy this problem, asset managers or index providers impose absolute and/or relative deconcentration constraints. But the cure is often worse than the illness, because this set of rigid ad-hoc constraints is in fact the veritable driver of the performance of minimum-volatility strategies without there being any academic justification whatsoever for the nature or value of the constraints chosen, which depend more in this case on in-sample calibration than on a concern for out-of-sample robustness. Sold with an objective of efficient diversification, in many cases minimum-volatility strategies hardly use the portfolio decorrelation budget and have fairly low levels of diversification and thus high degrees of idiosyncratic risk, the diversifiable risk that is not rewarded according to standard asset pricing theory.

Low volatility strategies

The typical Low Volatility strategy does not rely on an optimisation procedure but instead selects stocks with low historical volatility and then applies an ad-hoc weighting scheme that may or may not take into account differences in the individual volatilities of selected stocks. For illustration; capitalisation-weighting disregards individual volatilities whereas inverse volatility (as used by the S&P 500 Low Volatility Index) or variance as well as volatility-tilted capitalisation weighting let individual volatilities impact constituent weights.

Such Low Volatility approaches rely solely on low-volatility stocks, which should be beneficial if such stocks carry better risk-adjusted rewards than stocks that are more volatile. That is the premise of factor investing strategies tilting towards Low Risk stocks. Note that these approaches disregard the potential of volatility reduction that lies in correlations between securities. Naturally, ignoring correlations has practical advantages since the number of correlation coefficients in a universe of stocks increases with the squared number of stocks and correlation estimates are hard to estimate reliability (Longin and Solnik, 1995).

As is usually the case with industry implementations of factor investing, narrow factor-based stock selections and the use of weighting schemes favouring concentration lead to highly-concentrated portfolios, which have been documented to exhibit high turnover and a strong proportion of specific volatility (e.g. Amenc et al. 2016). Ultimately, these strategies that are explicitly exposed to low-volatility stocks suffer from the same defect as minimum volatility-type strategies, their high degree of concentration, which deprives them of one of the clear benefits of Modern Portfolio Theory since the seminal work of Harry Markowitz: diversification.

Addressing the concentration issue

Minimum volatility strategies

Irrespective of whether an investor regards low volatility stocks as attractive or unattractive, it is clear that the traditional minimum volatility strategy leads to poorly diversified portfolios and does not fully exploit correlations. As mentioned, popular implementations of low volatility strategies can be just as concentrated and disregard correlations completely.

Various approaches have been proposed to remedy the concentration issue of optimisation-based strategies, the most straightforward being to impose weight constraints. Imposing rigid security-level bounds reduces the ability of the optimiser to exploit the information in the variance-covariance matrix, but can help to obtain more "reasonable" portfolios: absolute upper bounds promote diversification while lower bounds reduce implementation costs by doing away with small holdings. In addition, security-level upper bounds couched in relative terms, i.e. as multiples of security-level weights within the capitalisation-weighted index of the underlying universe, are used to reduce concentration in small (and typically less liquid) securities. Portfolio-level weight constraints are also routinely used to reduce country and sector biases, although this can exacerbate the concentration issue at the security level. It should be underlined that, as more constraints are added, the solution is taken further away from the theoretically optimal portfolio. More worryingly, this makes the performance of the resulting portfolios highly sensitive to the choice of constraints, which comes with significant robustness risk. Indeed, choosing constraints to produce excellent in-sample performance will typically lead to disappointing out-of-sample results (on the effects of back-test over-fitting on out-of-sample performance, refer to Bailey, Borwein, López de Prado, and Zhu, 2014).

A more flexible approach has been introduced by EDHEC-Risk Institute Professor Raman Uppal and his co-authors. The "norm constraints" in DeMiguel, Garlappi, Nogales, and Uppal (2009) limit the overall amount

of concentration at the portfolio level, e.g. by constraining the sum of squared weights, rather than imposing caps on all stocks individually. The authors show that using such flexible concentration constraints instead of rigid upper and lower bounds on individual stock weights allows for a better use of the correlation structure. The approach is found to produce portfolios that typically have higher out-of-sample Sharpe ratios than competing approaches. This is the approach that ERI Scientific Beta has selected for its Efficient Minimum Volatility weighting scheme.

Low volatility strategies

The concentration of traditional low volatility strategies (and of other factor-based strategies) is caused by explicit choices of narrow factor-based selections and/or concentrated weighting schemes that aim to maximise the factor scores of portfolios. This concentration issue does not arise in the context of diversified factor-tilted solutions, where one relies on broad security selections and diversified weighting schemes. Diversified factor-tilted indices enjoy reduced exposure to idiosyncratic and other non-rewarded risks of all kinds, including relative industry and country biases; mitigate the risk of concentration into small and illiquid securities; and reduce turnover from changes in security-level factor scores (since broad factor-based selections are more stable and score-blind diversification strategies are unaffected by changes in scores). While the investment industry has favoured concentrated factor tilts, the seminal empirical and theoretical literature on factor investing underlines the importance of diversification and no case has been made in support of inefficient factor-tilted portfolios.

'... more robust performance is built on ...diversification of defensive strategies'

On the contrary and from a theoretical standpoint, Cochrane (1999) emphasises that any portfolio should be constructed so as to provide the efficient risk-return trade-off, in a mean-variance sense, at a given level of factor exposure. Fama (1996) shows that rewarded factors can be understood as multi-factor mean-variance efficient portfolio themselves. From an empirical standpoint, Amenc et al. (2016) find that, for a given breadth of selection, diversified portfolios deliver higher returns and risk-adjusted returns and have higher probabilities of outperforming the broad market than capitalisation-weighted portfolios. Analysed in the Carhart framework, they produce much higher alphas and alphas per unit of residual standard deviation and higher reduction in idiosyncratic volatility. They also observe that moving from a broad (half-universe) to a narrow (quintile) selection produces higher gross returns. It also increases volatility and tracking error, resulting in at best marginal gains in risk-adjusted performance before taking into account the costs of severely heightened turnover and reduced liquidity associated with narrower selections. In the end, they document that the benefits of (naively) diversifying factor-tilted portfolios based on broad selections far outweigh those of shifting to narrow selections while remaining cap-weighted. Such diversified factor-tilted portfolios produce much better performance and risk-adjusted performance in the medium and the long term while only marginally impacting turnover.

Conclusion

For EDHEC Risk Institute and ERI Scientific Beta, constructing a robust defensive strategy involves integration of the risk of excessive concentration and of the poor diversification of specific risk, which is very present in traditional approaches and offerings for both minimum volatility indices and low volatility factor indices. In recent months, investors have focused on the overpricing of low volatility stocks, without this overpricing being the subject of genuine academic consensus[5], and have continued to neglect the problem of the excessive concentration and poor diversification of low volatility portfolios, which the low volatility strategies based on fundamental weighting do not solve for example. Our research (Amenc, Ducoulombier and Lodh, 2016) summarised in the following article shows that better and more robust performance is built on this point of improving the diversification of defensive strategies.

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[5] While the rationale for a reward to holding low risk (low beta or low volatility) stocks is based on an ample amount of peer reviewed academic evidence, claims that the low volatility effect exists solely because of increasing overpricing are solely based on providers' brochures and absent from the body of peer reviewed academic evidence. It should also be noted that, even in principle, it is unclear how the low risk effect which has been documented consistently on long term US equity data (close to a century of data), international equity data and other asset classes, could be driven by "overpricing" which by definition should be a short term phenomenon. For further reasons to reject claims about overpricing of factors, we refer to Asness (2016).

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Smart factor indices and defensive strategies

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Introduction

Having discussed the different theoretical foundations and construction steps underpinning Minimum Volatility and Low Volatility strategies in the preceding article in this issue, we introduce alternative approaches to limiting concentration in Minimum and Low Volatility strategies in the current article. On the basis of this deconcentration objective, the article introduces ERI Scientific Beta's Smart Beta 2.0 framework, the principle of which is to reconcile a choice of factor exposure (here, low volatility) and to obtain a portfolio representing this factor choice that is not only deconcentrated but also very well diversified. We describe how the framework provides Smart Factor Indices that are consistent with both modern portfolio theory and the factor investing literature since they represent well-diversified portfolios that are tilted along the desired factor dimensions. The article also shows how to implement Low Volatility and Minimum Volatility strategies with Smart Factor Indices tilted towards the Low Risk factor, documents their risk and performance using 45 years of US large and mid-cap data and provide comparisons with popular defensive indices over 10 years for both US and Developed Markets as a whole.

Understanding smart factor indices

Consistent with the academic literature on factor-investing and modern portfolio theory, the ERI Scientific Beta Smart Factor Indices are designed to be efficient factor proxies. As such, they do not seek to maximise factor exposures but instead to achieve higher than median exposures to the desired rewarded factors while ensuring a high degree of diversification of idiosyncratic risks. This allows Smart Factor Indices to deliver high and robust risk-adjusted returns and to guarantee high investability and low implementation costs. It also offers the opportunity to control other non-rewarded risks such as sector or country risk without jeopardising performance.

All ERI Scientific Beta Smart Factor Indices are constructed with a two-step process which is at the heart of the Smart Beta 2.0 approach promoted by EDHEC-Risk Institute: (i) factor-tilting towards the targeted priced factor by way of broad stock selection (half-universe) and; (ii) application of a smart beta diversification strategy to the selection. As documented by Amenc et al. (2014), this allows the long-term premia associated with the desired factor tilts to be harvested efficiently while also reducing the contribution of unrewarded or specific risks to short-term volatility and tracking error. Stock-specific risk is reduced through the use of a suitable diversification strategy and the combination of strategies reduces the model risks inherent in single diversification strategies. As illustrated in Exhibit 1 on Page 16, five diversification strategies are available for ERI Scientific Beta single-strategy Smart Factor Indices and their equal-weighted combination is available as the weighting scheme underlying ERI Scientific Beta's off-the-shelf Multi-Strategy Smart Factor Indices.

Owing to the joint use of broad selections and of weighting schemes that ensure that opportunities for diversification of specific risk present in each selection be used, the ERI Scientific Beta Smart Factor methodology avoids or reduces issues associated with concentration (arising from optimisation and factor exposure maximisation approaches), notably high average and extreme idiosyncratic risks, undesired biases, high turnover, capacity and liquidity issues and high susceptibility to errors. Additional capacity/liquidity adjustments and optimal turnover control are applied to further increase investability of the indices and reduce replication costs.[6]

> *'Smart Factor Indices deliver high and robust risk-adjusted returns'*

Smart Factor Indices deliver significant added value above cap-weighted factor-tilted stock selections. For illustration, Exhibit 2 below compares the US 45-year risk and performance profiles of the off-the-shelf Multi-Strategy Smart Factor Indices (DMS for Diversified Multi-Strategy in the table) tilted towards strategic factors, to that of the identical stock selections weighted by capitalisation (CW in the table). Note that the gain in returns and risk-adjusted returns is particularly strong for Low Volatility strategies. Indeed, the capitalisation-weighted Low Volatility selection outperforms the broad-market index by only 32 basis points (bp) per annum (p.a.) while the Low Volatility Diversified Multi-Strategy Index delivers 255 bp p.a. above the same benchmark. In addition, the volatility of the Low Volatility Diversified Multi-Strategy Index is only 90% of that of the

[6] Sector and country neutrality can also be imposed on off-the-shelf multi-strategy indices as well as customised indices.

Exhibit 1: Overview of Popular Equity Diversification Strategies

The table indicates, for the diversification strategies, the optimisation objective (without taking into account any constraints, turnover control or liquidity rules), its unconstrained solution and the required parameters. The "Optimality conditions" column indicates under which conditions each diversification strategy would result in the Maximum Sharpe Ratio portfolio from Modern Portfolio Theory. N is the number of stocks, μ_i is the expected return on stock i, σ_i is the volatility for stock i, ρ_{ij} is the correlation between stocks i and j, μ is the (Nx1) vector of expected returns, 1 is the (Nx1) vector of ones, σ is the (Nx1) vector of volatilities, Ω is the (NxN) correlation matrix and Σ is the (NxN) covariance matrix. $\lambda_i = \frac{(\mu_i - R_f)}{\sigma_i}$ is the Sharpe ratio of Stock i, R_f is the risk-free rate.

Strategy	Objective	Unconstrained closed-form solution	Required parameter(s)	Optimality conditions
Maximum Deconcentration	Maximise effective number of stocks	$w^* = \frac{1}{N}\mathbb{1}$	None	$\mu_i=\mu$ □i $\sigma_i=\sigma$ □i $\rho_{ij}=\rho$ □i
Diversified Risk Parity	Equalise risk contributions under "Constant Correlation" assumption	$w^* = \frac{diag(\sigma^{-1})}{\mathbb{1}'diag(\sigma^{-1})}$	σ_i	$\lambda_i=\lambda$ □i $\rho_{ij}=\rho$ □i
Maximum Decorrelation	Minimise the portfolio volatility under the assumption of identical volatility across all stocks.	$w^* = \frac{\Omega^{-1}\mathbb{1}}{\mathbb{1}'\Omega^{-1}\mathbb{1}}$	ρ_{ij}	$\mu_i=\mu$ □i $\sigma_i=\sigma$ □i
Efficient Minimum Volatility	Minimise portfolio volatility	$w^* = \frac{\Sigma^{-1}\mathbb{1}}{\mathbb{1}'\Sigma^{-1}\mathbb{1}}$	σ_i, ρ_{ij}	$\mu_i=\mu$ □i
Efficient Maximum Sharpe Ratio	Maximise portfolio Sharpe ratio	$w^* = \frac{\Sigma^{-1}\mu}{\mathbb{1}'\Sigma^{-1}\mu}$	μ_i, σ_i, ρ_{ij}	Optimal by construction

capitalisation-weighted selection. Thus, higher excess returns and lower volatility both contribute to producing a superior Sharpe ratio for the Low Volatility Diversified Multi-Strategy Index relative to that of the capitalisation-weighted Low Volatility selection; these are 0.37 and 0.57, respectively.

ERI Scientific Beta Smart Factor Indices also typically outperform factor indices put forward by other index providers that do not benefit from the clear separation between choice of factor and choice of diversification method or fail to optimise diversification of idiosyncratic risks. It is on the basis of this smart factor approach, which combines an explicit choice of factor exposure with the benefits of diversifying the stocks that correspond to this factor exposure, which ERI Scientific Beta proposes to revisit the traditional defensive strategies.

Implementing low volatility and minimum volatility strategies with smart factor indices

ERI Scientific Beta uses total volatility to rank individual stocks for factor-tilting, which is not only consistent with the work of Ang et al. (2006, 2009) on total volatility, but also with their results on idiosyncratic volatility (since it represents the lion's share of total volatility at the individual stock level) and with the systematic risk approach of Frazzini and Pedersen (2014) (because low beta stocks tend to be Low Volatility stocks in the cross section and vice versa). Exhibits 3-5 compare the performance of two ERI Scientific Beta Low Volatility Smart Factor Indices to that of popular defensive indices for the U.S. and the Developed World. These two indices correspond to two different approaches to Low Volatility strategies.

The Scientific Beta Low Volatility Multi-Strategy Indices are intended to capture the Low Risk factor, while being highly diversified. This diversification is guaranteed by equally weighting five diversification methods whose combination, as was shown in Amenc et al. (2014), produces an excellent level of risk-adjusted performance. This quality of diversification is explained by the fact that each of the weighting schemes used presents different model risks (optimality and estimation error risks)[7] as shown in Exhibit 1 and is associated with different biases and conditionality. Combining multiple weighting schemes not only diversifies the aforementioned model risks, providing more robust diversification, but also allows investors to avail of the benefits of the decorrelation between the various diversification strategies that result from these weighting models.

The Scientific Beta Low Volatility Efficient Minimum Volatility indices do not seek to maximise diversification of the specific risk, but instead aim to maximise the defensive nature of the strategy while maintaining a high degree of diversification, and notably by using a state-of-the-art norm constraint deconcentration method[8]. Applying a deconcentration method enables a defensive but well-diversified index to be constructed, since, unlike traditional

[7] For more on the benefits of diversifying weighting schemes, please refer to Amenc et al. (2015), Robustness of Smart Beta Strategies; and Martellini, Milhau and Tarelli (2014), Estimation Risk versus Optimality Risk: an Ex-Ante Efficiency Analysis of Heuristic and Scientific Equity Portfolio Diversification Strategies. These White Papers are available at http://docs.scientificbeta.com/Library/External/White_Papers/ERI_Scientific_Beta_Publication_Robustness_Smart_Beta_Strategies; and http://docs.scientificbeta.com/Library/External/Research_Publications/ERI_Scientific_Beta_Publication_Estimation_Risk_vs_Optimality_Risk.

[8] The Efficient Minimum Volatility weighting scheme uses the norm-constraint approach and targets an effective number of stocks equal to one third of the eligible stocks. Concentration induced by the other optimisation-based strategies is limited through weight adjustments to ensure that all securities are included, but that no security is given a dominant weighting.

Exhibit 2: Performance of Capitalisation-Weighted vs. Multi-Strategy-diversified Factor Selections

The analysis is based on daily total return data in USD from 31 December 1970 to 31 December 2015 (45 years). The benchmark is the cap-weighted portfolio of all stocks in the USA universe. The Scientific Beta LTTR USA universe consists of the largest 500 USA stocks. Mid Cap, Positive Momentum, Low Volatility, Value, Low Investment and High Profitability selections all represent 50% of stocks with such characteristics in a U.S. universe of 500 stocks. The risk-free rate is the return of the 3-month U.S. Treasury Bill. 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. 95% Tracking Error is the 95th percentile of 1-year rolling tracking error. It is computed using a 1-year rolling window and a 1-week step size. The probability of outperformance is the probability of obtaining positive excess returns from investing in the strategy for a period of 1, 3 or 5 years at any point during the history of the strategy. Rolling windows of 1, 3 and 5 years and a 1-week step size are used. Source: www.scientificbeta.com.

31 December 1970 to 31 December 2015		Mid Cap		Positive Momentum		Low Volatility		Value		Low Investment		High Profitability	
	Broad CW	CW	DMS	CW	DMS	CW	DMS	CW	DMS	CW	DMS	CW	DMS
Ann. Returns	10.45%	12.97%	14.22%	11.39%	13.39%	10.76%	13.00%	11.90%	14.28%	12.32%	14.01%	10.79%	12.99%
Ann. Volatility	16.88%	17.09%	15.80%	17.26%	16.01%	15.39%	13.85%	17.17%	15.67%	15.83%	14.93%	17.02%	15.73%
Sharpe Ratio	0.32	0.46	0.58	0.37	0.52	0.37	0.57	0.40	0.59	0.46	0.60	0.34	0.50
Max Drawdown	54.63%	57.09%	53.42%	50.81%	53.25%	51.10%	48.31%	60.01%	53.75%	51.12%	50.82%	52.29%	48.86%
Effective Number	114	188	188	64	198	65	200	69	189	59	187	55	199
Ann. Rel. Returns	-	2.52%	3.77%	0.94%	2.95%	0.32%	2.55%	1.45%	3.84%	1.87%	3.57%	0.34%	2.54%
Ann. Tracking Error	-	5.72%	6.42%	3.49%	4.84%	4.27%	5.99%	4.42%	5.47%	3.79%	5.42%	3.22%	4.35%
95% Tracking Error	-	9.27%	11.54%	6.24%	8.59%	8.18%	11.38%	8.12%	10.03%	6.58%	9.88%	6.48%	7.20%
Information Ratio	-	0.44	0.59	0.27	0.61	0.07	0.43	0.33	0.70	0.49	0.66	0.11	0.58
Outperf Prob. (1Y)	-	61.6%	66.6%	62.8%	66.3%	50.8%	63.5%	58.9%	69.2%	62.1%	70.3%	50.6%	68.0%
Outperf Prob. (3Y)	-	69.4%	75.7%	71.3%	75.7%	52.7%	75.7%	68.7%	79.5%	77.7%	82.0%	51.7%	78.9%
Outperf Prob. (5Y)	-	75.9%	81.5%	81.1%	87.0%	58.4%	86.9%	67.5%	89.0%	89.1%	89.9%	58.5%	85.6%
Max Rel. DD	-	35.94%	42.06%	14.44%	17.28%	33.82%	43.46%	20.31%	32.68%	26.47%	38.49%	24.52%	25.21%
1-Way Turnover	3.1%	19.3%	27.4%	58.1%	67.1%	10.0%	26.2%	14.6%	25.3%	26.1%	33.7%	5.4%	23.0%

'The Scientific Beta indices aim to maximise the defensive nature of the strategy while maintaining a high degree of diversification'

rigid constraints, this approach favours better use of the diversification potential offered by correlations between stocks. This is all the more so when the Efficient Minimum Volatility approach is applied to a selection of Low Volatility stocks as this reduces the ability of the optimiser to simply select Low Volatility stocks to meet its objective and forces it to make better use of the information in the correlation matrix.

The historical out-of-sample simulations over both long and short periods confirm that the objectives of these indices are met and show notably that the Scientific Beta Low Volatility Efficient Minimum Volatility Indices present a more defensive character than the Scientific Beta Low Volatility Diversified Multi-Strategy Indices whose Diversified Multi-Strategy approach produces relative performance that is less affected by market direction. In both cases, through their superior diversification qualities, these indices exhibit remarkable risk-adjusted performance that is of course superior to that of traditional defensive strategies.

As shown in Exhibit 3, over the 45 years of the long-term track record and relative to the capitalisation-weighted benchmark, the ERI Scientific Beta Low Volatility Multi-Strategy index has a beta of 0.80 and produces a volatility reduction of around 18% while the more defensive ERI Scientific Beta Low Volatility Efficient Minimum Volatility index has a beta of 0.74 and yields a volatility reduction of 23%. The annualised outperformance of the ERI Scientific Beta Low Volatility Multi-Strategy and Efficient Minimum Volatility indices is 2.55% and 2.65%, respectively. The combination of higher performance and lower volatility translates into significant Sharpe ratio gains for these two solutions (78% and 91%, respectively).

It is important to note that over short and medium-term horizons, the ERI Scientific Beta Low Volatility Multi-Strategy index has a higher chance of outperforming the broad market benchmark than the ERI Scientific Beta Low Volatility Efficient Minimum Volatility index. This is consistent

Exhibit 3: Long-Term Track Record of ERI Scientific Beta Low Volatility Indices (United States)

The analysis is based on daily total return data in dollars from December 31, 1970 to December 31, 2015 (45 years). Regressions are performed using weekly total returns in dollars. The benchmark is the cap-weighted portfolio of all stocks in Scientific Beta U.S. Long-Term Track Record universe consisting of the 500 largest U.S. stocks. The risk-free rate is the return of the 3-month U.S. Treasury Bill. The 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. The 95% Tracking Error is the 95th percentile of 1-year rolling tracking error computed using a 1-year rolling window and a 1-week step size. The probability of outperformance is the probability of obtaining positive excess returns from investing in the strategy for a period of 1, 3, and 5 years at any point during the history of the strategy; rolling windows of 1, 3, and 5 years and a 1-week step size are used for the computation. Rolling Volatility statistics are reported as mean, standard deviation and 95th percentile of annualised volatility and computed using a 3-year rolling window and 1-week step size. Quarters with positive benchmark index returns are classed as bull quarters and the remaining are classed as bear quarters. The top 25% quarters with the best benchmark index returns are extreme bull quarters and the bottom 25% quarters with the worst benchmark index returns are extreme bear quarters. The returns on the market factor are the returns of the capitalisation-weighted benchmark over the risk-free rate. Reported turnover is 1-way, annual and it is averaged across 180 rebalancings in the 45-year period. Source: www.scientificbeta.com.

31-Dec-1970 to 31-Dec-2015 (45 Years)	Scientific Beta Long-Term United States Capitalisation Weighted	SciBeta Long-Term United States Low-Volatility Diversified Multi-Strategy	SciBeta Long-Term United States Low-Volatility Efficient Minimum Volatility
Ann. Returns	10.45%	13.00%	13.10%
Ann. Volatility	16.88%	13.85%	13.04%
Sharpe Ratio	0.32	0.57	0.61
Max Drawdown	54.63%	48.31%	42.42%
Ann. Rel. Returns	-	2.55%	2.65%
Ann. Tracking Error	-	5.99%	6.98%
95% Tracking Error	-	11.38%	13.77%
Information Ratio	-	0.43	0.38
Outperf Prob. (1Y)	-	63.47%	59.12%
Outperf Prob. (3Y)	-	75.70%	74.15%
Outperf Prob. (5Y)	-	86.88%	81.86%
Max Relative Drawdown	-	43.46%	46.94%
3-Year Rolling Vol Mean	16.36%	13.38%	12.64%
3-Year Rolling Vol Std	5.23%	4.38%	3.97%
3-Year Rolling Vol 95%	29.22%	24.57%	22.05%
Ann. Rel. Returns Bull	-	-0.91%	-2.12%
Ann. Rel. Returns Bear	-	7.43%	9.56%
Ann. Rel. Returns Extreme Bull	-	-6.18%	-9.37%
Ann. Rel. Returns Extreme Bear	-	7.24%	9.47%
CAPM Market Beta	1.00	0.80	0.74
1-Way Turnover	3.1%	26.2%	34.2%

with the stronger downside protection associated with the ERI Scientific Beta Low Volatility Efficient Minimum Volatility index and the better upside capture of the ERI Scientific Beta Low Volatility Multi-Strategy index. The latter's lower tracking error, which is derived from diversifying across weighting schemes and achieving lower bull/bear conditionality, contributes to its higher information ratio relative to the ERI Scientific Beta Low Volatility Efficient Minimum Volatility index (0.43 vs. 0.38). Extreme risk figures are consistent with these differences in conditionality: the ERI Scientific Beta Low Volatility Multi-Strategy index has higher drawdown but lower relative drawdown than the ERI Scientific Beta Low Volatility Efficient Minimum Volatility index.

Exhibit 4 summarises the performance of the two ERI Scientific Beta United States Low Volatility indices and two third-party indices – the MSCI USA Minimum Volatility Index and the S&P 500 Low Volatility Index – over a period of 10 years using the S&P 500 index as benchmark. Within a universe of US large and mid cap stocks, the MSCI USA Minimum Volatility Index uses a proprietary Barra Optimiser to determine the portfolio with the lowest total risk subject to a series of ad-hoc constraints and using an estimated co-variance matrix. Constraints include (but are not limited to) minimum and maximum weights for each included security,

'Explicit targeting of Low Volatility stocks and superior diversification of specific risk explain the superior performance of the ERI Scientific Beta Low Volatility index'

Exhibit 4: Risk and Performance of ERI Scientific Beta Low Volatility Indices and Comparables (United States, 10 Years)

The analysis is based on daily total return data in dollars from December 31, 2005 to December 31, 2015 (10 years). Regressions are performed using weekly total returns in dollars. The benchmark is the S&P 500 index. The Scientific Beta US universe consists of the 500 largest US stocks. The risk-free rate is the return of the 3-month U.S. Treasury Bill. The 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. The 95% Tracking Error is the 95th percentile of 1-year rolling tracking error and is computed using a 1 week step size. The probability of outperformance is the probability of obtaining positive excess returns from investing in the strategy for a period of 1, 3 or 5 years at any point during the history of the strategy; rolling windows of 1, 3, and 5 years and a 1-week step size are used for the computation. Rolling Volatility statistics are reported as mean, standard deviation and 95th percentile of annualised volatility and computed using a 3-year rolling window and 1-week step size. Quarters with positive benchmark index returns are classed as bull quarters and the remaining are classed as bear quarters. The top 25% quarters with the best benchmark index returns are extreme bull quarters and the bottom 25% quarters with the worst benchmark index returns are extreme bear quarters. The returns on the market factor are the returns of the capitalisation-weighted benchmark over the risk-free rate. Reported turnover is 1-way, annual and it is averaged across 40 rebalancings in the 10-year period. Source: www.scientificbeta.com and Bloomberg.

31-Dec-2005 to 31-Dec-2015 (10 Years)	S&P 500	SciBeta U.S. Low Volatility Diversified Multi-Strategy	SciBeta U.S. Low Volatility Efficient Minimum Volatility	MSCI USA Minimum Volatility	S&P500 Low Volatility
Ann. Returns	7.28%	9.62%	10.54%	8.86%	9.35%
Ann. Volatility	20.71%	17.25%	15.70%	17.14%	15.28%
Sharpe Ratio	0.30	0.49	0.60	0.45	0.54
Max Drawdown	55.25%	48.31%	42.42%	46.61%	40.40%
Ann. Rel. Returns	-	2.34%	3.26%	1.58%	2.07%
Ann. Tracking Error	-	5.25%	7.00%	5.32%	8.54%
95% Tracking Error	-	9.67%	13.87%	8.39%	17.71%
Information Ratio	-	0.45	0.47	0.30	0.24
Outperf Prob. (1Y)	-	62.55%	65.74%	57.66%	50.21%
Outperf Prob. (3Y)	-	91.80%	86.89%	74.86%	69.67%
Outperf Prob. (5Y)	-	99.24%	95.04%	79.01%	73.28%
Max Relative Drawdown	-	8.79%	12.30%	12.83%	18.75%
3-Year Rolling Vol Mean	21.74%	17.91%	16.33%	17.62%	15.76%
3-Year Rolling Vol Std	7.04%	6.02%	5.13%	6.47%	4.72%
3-Year Rolling Vol 95%	30.61%	25.48%	22.83%	25.79%	21.72%
Ann. Rel. Returns Bull	-	-2.20%	-3.28%	-4.64%	-6.59%
Ann. Rel. Returns Bear	-	8.54%	12.49%	10.37%	14.78%
Ann. Rel. Returns Extreme Bull	-	-8.03%	-11.69%	-9.48%	-14.89%
Ann. Rel. Returns Extreme Bear	-	9.15%	13.91%	11.97%	16.13%
CAPM Market Beta	1.00	0.82	0.74	0.80	0.68
1-Way Turnover	NA	28.2%	36.0%	NA	NA

minimum and maximum constituent sector weights relative to the parent index and turnover limits. The S&P 500 Low Volatility index selects the 100 least volatile stocks in the S&P 500 universe based on their past one-year price volatility and weights these by the inverse of their volatilities to produce a very defensive (and highly concentrated) index. No constraints are applied.

While being a factor-harvesting solution that acquires a defensive profile in a long-only implementation, the ERI Scientific Beta US Low Volatility Multi-Strategy index produces volatility reduction of about 17% (with respect to the S&P 500 index benchmark), on par with the MSCI USA Minimum Volatility index. Providing somewhat lower downside protection but significantly better upside capture, it produces higher returns and Sharpe ratio and an information ratio that is about 1.5 times that of the MSCI USA Minimum Volatility. Due (primarily) to its more pronounced defensive character relative to the Scientific Beta U.S. Low Volatility Multi-Strategy index, the MSCI USA Minimum Volatility index experiences longer and more severe underperformance (in periods dominated by bullish markets). Using rolling window analysis to span the available return history, the probability of outperformance measures how often the strategy has managed to outperform its benchmark for a given holding period. Although the 2006-2015 decade has been marked by two significant bear episodes, the Scientific Beta US Low Volatility Multi-Strategy index shows a significantly higher probability of outperformance for a one-year holding period than the comparable MSCI index (62.55% vs. 57.66%) and vastly superior three- and five-year performances (91.8% vs. 74.86% and 99.24% vs. 79.01%, respectively).

The ERI Scientific Beta Low Volatility Efficient Minimum Volatility index and the S&P 500 Low Volatility index

Exhibit 5: Risk and Performance of ERI Scientific Beta Low Volatility Indices and Comparables (Developed Markets, 10 Years)

The analysis is based on daily total return data in dollars from 31 December 2005 to 31 December 2015 (10 years). Regressions are performed using weekly total returns in dollars. The benchmark is the MSCI World Index. The Scientific Beta Developed universe consists of 2,000 large and mid-cap stocks. The risk-free rate is the return of the 3-month U.S. Treasury Bill. The 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. 95% Tracking Error is the 95th percentile of 1-year rolling tracking error and is computed using a 1-week step size. The probability of outperformance is the probability of obtaining positive excess returns from investing in the strategy for a period of 1, 3 or 5 years at any point during the history of the strategy; rolling windows of 1, 3, and 5 years and a 1-week step size are used for the computation. Rolling Volatility statistics are reported as mean, standard deviation and 95th percentile of annualised volatility and computed using a 3-year rolling window and 1-week step size. Quarters with positive benchmark index returns are classed as bull quarters and the remaining are classed as bear quarters. The top 25% quarters with the best benchmark index returns are extreme bull quarters and the bottom 25% quarters with the worst benchmark index returns are extreme bear quarters. The returns on the market factor are the returns of the capitalisation-weighted benchmark over the risk-free rate. Reported turnover is 1-way, annual and it is averaged across 40 rebalancings in the 10-year period. Source: www.scientificbeta.com and Bloomberg.

31-Dec-2005 to 31-Dec-2015 (10 Years)	MSCI World	SciBeta Developed Low Volatility Diversified Multi-Strategy	SciBeta Developed Low Volatility Efficient Minimum Volatility	MSCI World Minimum Volatility	S&P GIVI Developed
Ann. Returns	5.54%	8.58%	9.35%	7.30%	6.52%
Ann. Volatility	17.80%	13.98%	12.86%	12.81%	15.62%
Sharpe Ratio	0.25	0.53	0.64	0.48	0.35
Max Drawdown	57.46%	49.55%	45.02%	47.35%	53.11%
Ann. Rel. Returns	-	3.04%	3.81%	1.76%	0.98%
Ann. Tracking Error	-	4.83%	6.19%	6.74%	3.30%
95% Tracking Error	-	9.24%	12.29%	10.95%	6.25%
Information Ratio	-	0.63	0.62	0.26	0.30
Outperf Prob. (1Y)	-	65.53%	68.09%	56.60%	56.81%
Outperf Prob. (3Y)	-	96.99%	93.17%	74.59%	87.16%
Outperf Prob. (5Y)	-	100.00%	97.33%	79.01%	94.27%
Max Relative Drawdown	-	9.76%	13.43%	17.42%	5.75%
3-Year Rolling Vol Mean	18.92%	14.73%	13.53%	13.27%	16.51%
3-Year Rolling Vol Std	5.32%	4.16%	3.68%	4.44%	4.76%
3-Year Rolling Vol 95%	25.44%	19.82%	18.07%	18.82%	22.33%
Ann. Rel. Returns Bull	-	-1.28%	-2.41%	-6.16%	-1.49%
Ann. Rel. Returns Bear	-	8.58%	12.08%	12.73%	4.10%
Ann. Rel. Returns Extreme Bull	-	-7.74%	-11.54%	-13.99%	-4.10%
Ann. Rel. Returns Extreme Bear	-	10.05%	14.09%	14.72%	4.38%
CAPM Market Beta	1.00	0.78	0.71	0.69	0.88
1-Way Turnover	NA	29.5%	36.4%	NA	NA

are significantly more defensive than the previous two indices and provide volatility reductions of 24% and 26%, respectively. Conditional analysis shows that the ERI Scientific Beta Low Volatility Efficient Minimum Volatility index provides less downside protection but much better upside capture than the S&P 500 Low Volatility index. Note that, relative to the MSCI USA Minimum Volatility index, the ERI Scientific Beta Low Volatility Efficient Minimum Volatility index not only provides more downside protection but also achieves better upside capture. The ERI Scientific Beta Low Volatility Efficient Minimum Volatility index exhibits the highest returns and risk-adjusted returns of the four defensive U.S. indices compared here and its Sharpe ratio of 0.60 is twice that of the broad equity market over the period. Despite its (desired) high bull/bear conditionality, the ERI Scientific Beta Low Volatility Efficient Minimum Volatility index has an information ratio of 0.47, almost twice that of the S&P 500 Low Volatility index. Furthermore, it produces vastly superior outperformance probabilities over the short and medium term than what its S&P Dow Jones counterpart (65.74% vs. 50.21% for a one-year holding period, 86.89% vs. 69.67% over three years and 95.04% vs. 73.28% over five years) or for that matter than the MSCI USA Minimum Volatility index.

The relative profile of the two ERI Scientific Beta Low Volatility indices is consistent with what was observed with the long-term track records. The ERI Scientific Beta Low Volatility Efficient Minimum Volatility index is more defensive and shows more bull/bear conditionality. While its more defensive profile serves it particularly

well in the decade, it nevertheless shows lower probabilities of outperformance than its multi-strategy counterpart over the medium term. Again, the extreme risk indicators are consistent with this positioning: the Scientific Beta Low Volatility Efficient Minimum Volatility index has significantly lower drawdown but higher relative drawdown than the multi-strategy index.

Exhibit 5 extends the comparison across defensive strategies to developed markets as a whole, where the MSCI World index serves as the broad capitalisation-weighted benchmark. We compare the MSCI World Minimum Volatility index and the S&P GIVI Developed index to the Scientific Beta Developed Low Volatility Multi-Strategy and Efficient Minimum Volatility indices. The MSCI World Minimum Volatility index is constructed using the same methodological principles as the MSCI USA Minimum Volatility index but subjected to additional country relative weight constraints. The S&P GIVI Developed index is based on the 25 developed countries in the S&P Global BMI. In each country, the stocks are sorted by their betas and the lowest beta stocks that represent 70% of that country's market capitalisation are selected. The selected stocks are weighted in proportion to their "intrinsic value," a metric which depends on book value and discounted projected earnings. Note that ERI Scientific Beta builds indices from the basic geographic block and developed indices are assembled by combining basic-block indices on the basis of each block's free-float capitalisation. This is consistent with the application of factor investing at the level of homogeneous regions and ensures the block-level geographic neutrality of multi-block indices. By construction, ERI Scientific Beta's developed smart beta indices have the same exposures to the US, Japan and the UK as their capitalisation-weighted reference and their geographic biases are limited to countries that are part of multi-country blocks (i.e. Developed Eurozone, Developed Europe ex UK ex Eurozone and Developed Asia-Pacific ex Japan).

Both Scientific Beta indices produce higher volatility reductions when applied to developed markets as a whole, but their relative profile and 10-year performance remain consistent with what was observed for the US. The ERI Scientific Beta Low Volatility Efficient Minimum Volatility index delivers volatility reduction of close to 28% while its multi-strategy counterpart reduces volatility by over 21%. Both Low Volatility Smart Factor indices deliver high excess returns in the 2006-2015 decade, with the more defensive index also producing significantly better returns for developed markets as a whole (3.81% p.a. vs. 3.04%). Both indices produce remarkable Sharpe ratio gains relative to the benchmark and have exceptional information ratios for defensive strategies. Sharpe ratios are 0.53 and 0.64 for the Developed Low Volatility Multi-Strategy and Efficient Minimum Volatility indices, respectively, to be compared to the market's 0.25, and the information ratios are 0.63 and 0.62, respectively. As observed in the US, the medium-term outperformance probabilities are higher for the ERI Scientific Beta Low Volatility Multi-Strategy index. The absolute and relative drawdown patterns are also fully consistent with the US track records.

While the MSCI World Minimum Volatility index produces volatility reduction and downside protection that are similar to those of the ERI Scientific Beta Developed Low Volatility Efficient Minimum Volatility index, it has relatively low upside capture. As a result, it underperforms its comparable ERI Scientific Beta index by over 2% p.a. over the period, delivers 75% of the latter's Sharpe ratio of 0.64 and 42% of its information ratio of 0.62. It also significantly underperforms the less defensive ERI Scientific Beta Developed Low Volatility Multi-Strategy index in terms of returns and risk-adjusted returns.

Owing to its mild volatility filtering, the S&P 500 GIVI Developed index is the least defensive of the four indices. However, its upside capture is lacklustre and, over the period, it posts meagre outperformance of 0.98% p.a. and a relatively modest Sharpe ratio gain. Its lower bull/bear conditionality is associated with tracking error that is about half that of the MSCI index, which it dominates in terms of information ratio. The said ratio is nevertheless less than half that of the ERI Scientific Beta indices. As observed with the US indices, the ERI Scientific Beta Low Volatility indices produce higher probabilities of outperformance over the short and medium term.

Explicit targeting of Low Volatility stocks and superior diversification of specific risk explain the superior performance of the ERI Scientific Beta Low Volatility index relative to peers. The Low Volatility Multi-Strategy indices are factor-harvesting solutions that acquire a defensive profile in a long-only implementation and trail the capitalisation-weighted benchmark reasonably in all but the strongest bull markets. The Low Volatility Efficient Minimum Volatility indices are designed to produce a strongly defensive character and as such generate sterling downside protection at a cost of reduced upside capture. This more defensive character causes the index to trail more significantly in bull markets, which leads to lower probabilities of outperformance over the medium term than what the Low Volatility Multi-Strategy indices deliver (Amenc et al. 2016).

The choice between the Scientific Beta Low Volatility Efficient Minimum Volatility index and the Scientific Beta Low Volatility Diversified Multi-Strategy index will therefore depend on the investor's level of risk aversion and more globally on their risk allocation objective. It is clear that if the objective is to introduce the Low Risk factor into the risk factor allocation menu, then the Scientific Beta Low Volatility Diversified Multi-Strategy index is the ideal candidate. On the other hand, if the objective is to obtain the lowest absolute risk for the equity allocation, then the Scientific Beta Low Volatility Efficient Minimum Volatility index will be favoured.

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Achieving dynamic defensive strategies

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Introduction

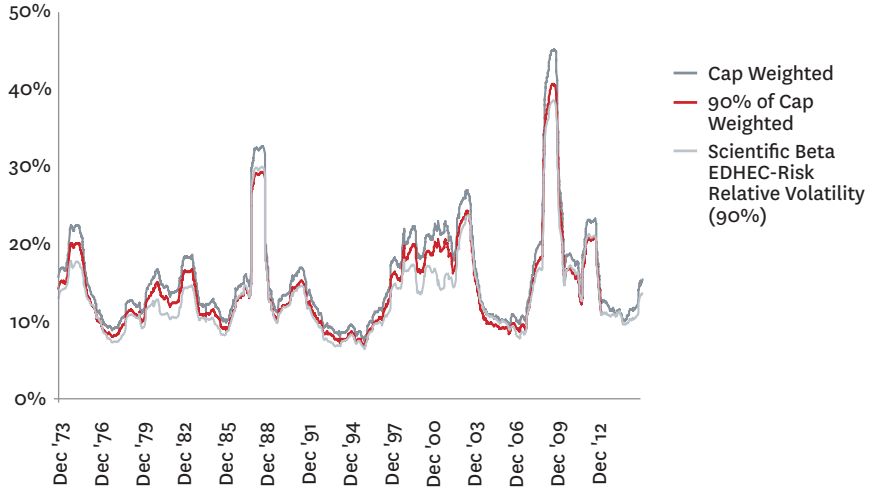
Even though it is possible to design defensive strategies that are well diversified on the specific risk level, and to produce smart factor low volatility indices that have good defensive capabilities and excellent long-term risk-adjusted performance, it must be recognised that these strategies remain concentrated in the low volatility factor by construction. Being concentrated in the Low Risk factor, traditional defensive strategies miss out on the rewards associated with other factor tilts. In addition, their design implies a constantly low exposure to market risk, which provides relative downside protection in bear markets but causes them to trail the broad-market capitalisation-weighted index in bull markets. In this article, we introduce the Scientific Beta Multi-Beta Multi-Strategy Relative Volatility (90%) solutions which rely on a risk-based allocation model engineered by EDHEC-Risk Institute to dynamically allocate to the whole range of ERI Scientific Beta Smart Factor Indices carrying long-term risk premia with a view to delivering a dissymmetric defensive profile.

Relying on the persistence of volatility and the negative relationship between volatility and returns, these benchmarks target a constant reduction in relative volatility that allows the defensive character of the strategy to adjust to market conditions. This is meant to achieve a high absolute reduction in volatility when market volatility is high and a low absolute reduction when market volatility is low. Because of the well documented negative relationship between volatility and returns, high volatility regimes tend to correspond to bear markets and low volatility regimes to bull markets. Hence, the solution seamlessly adjusts the risk budget to changing market conditions so as to provide significant downside protection with improved upside capture relative to traditional defensive strategies.

De facto, these solutions are derivations of the flagship Scientific Beta Multi-Beta Multi-Strategy indices, which equalise the allocation to the Scientific Beta Smart Factor Indices that correspond to the choices of factor tilts[9] (and

Exhibit 1: Realised 1-Year Rolling Volatility of the Scientific Beta Multi-Beta Multi-Strategy Relative Volatility (90%) solution (U.S. Long-Term Track Record)

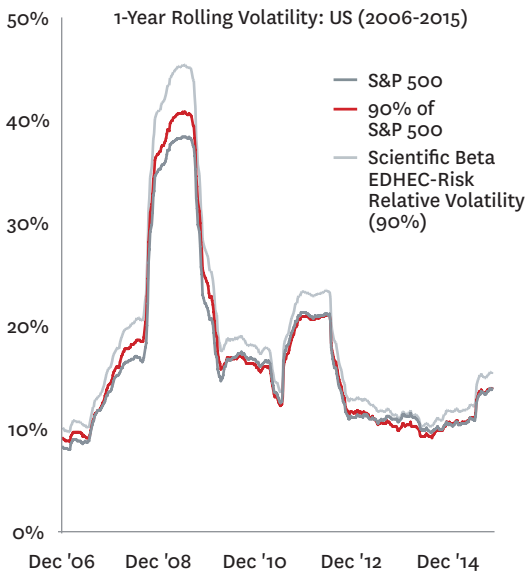
The analysis is based on daily total return data in dollars from 31 December 1972 to 31 December 2015 (43 years). The Rolling Volatility is computed using a rolling window of length 1 year and a 1-week step size. The Benchmark is the cap-weighted portfolio of all stocks in the Scientific Beta US LTTR universe, which consists of the 500 largest U.S. stocks. Scientific Beta US Long Term Smart Factor Indices have a 45-year track record. As the calibration of solutions requires 2 years, all US Long Term Smart Beta solutions have a 43-year track record. Source: www.scientificbeta.com.

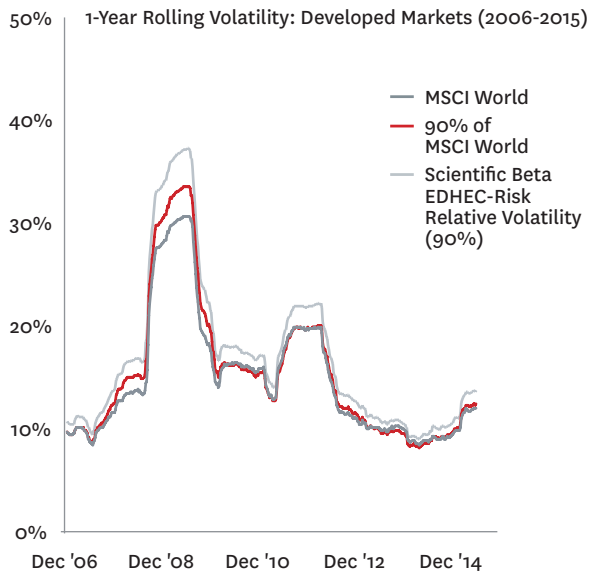


[9] Four factor tilts – Mid Cap, Value, Positive Momentum and Low Volatility – for the Scientific Beta MBMS 4-Factors (EW) Indices; two factor tilts – Low Investment and High Profitability – for the Scientific MBMS Quality Indices; and all six factor tilts for the Scientific Beta 6-Factor MBMS (EW) Indices.

Exhibit 2: Realised 1-Year Rolling Volatility of the Scientific Beta Multi-Beta Multi-Strategy Relative Volatility (90%) solution

Panel A: Scientific Beta US Indices - The benchmark is the S&P 500 Index. The Scientific Beta US universe consists of the 500 largest US stocks. Panel B: Scientific Beta Developed Indices – The benchmark is the MSCI World Index. The Scientific Beta Developed universe consists of 2,000 large and mid-cap stocks. The analysis is based on daily total return data in dollars from December 31, 2005 to December 31, 2015 (10 years). The Rolling Volatility is computed using a rolling window of length 1 year and a 1-week step size. Source: www.scientificbeta.com.





diversification strategies).[10] In the case of smart beta solutions, the goal is no longer a fixed equally-weighted mix between the Smart Factor Indices that make up these Multi-Beta Multi-Strategy indices, but dynamic risk allocation that is intended to respect the investor's absolute or relative risk objectives. The derivation applying to the Scientific Beta Multi-Beta Multi-Strategy Relative Volatility (90%) solution takes the Scientific Beta 6-Factor Multi-Beta Multi-Strategy Indices as a starting point. It therefore involves dynamic allocation drawing on the 30 indices (six factor tilts times five weighting schemes) that make up these indices.

The negative correlation between volatility and return

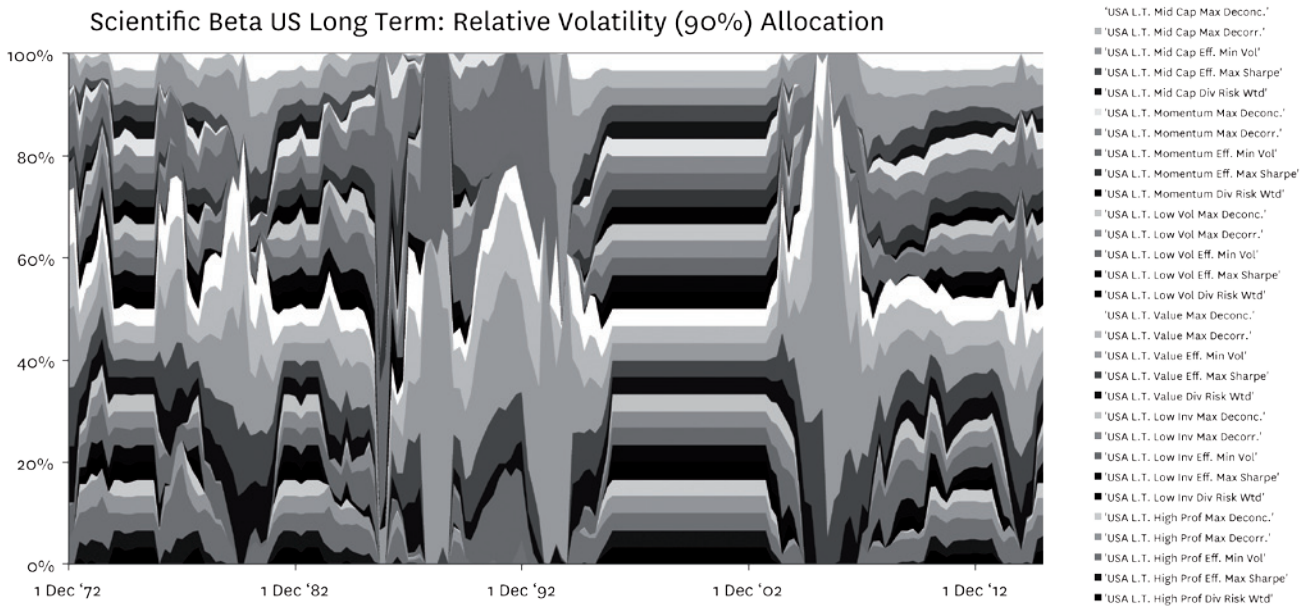
There is a long tradition in finance that models stock return volatility as being negatively correlated with stock returns. This is consistent with an empirical relationship first observed for United States markets (see for example the studies by Schwert, 1989, covering the period from 1834 to 1987 and Campbell and Hentschel, 1992, covering the period from 1926 to 1988) and for which there is also international empirical evidence, in particular for developed markets (see for example Li et al., 2005; Talpsepp and Rieger, 2010; and Dimitriou and Simos, 2011). Historically, there have been two main theoretical justifications for the asymmetric nature of volatility documented by empirical studies: leverage and volatility feedback. The leverage hypothesis, which can be traced to Black (1976) and Christie (1982), notes that, as asset prices decline, companies become more leveraged as the value of their debt rises relative to that of their equity. With increasing leverage, stocks become riskier, so it is to be expected that they be more volatile. The feedback effect is predicated on the persistence of volatility and the existence of a positive inter-temporal relation between expected return and conditional variance. Increased volatility raises required expected returns, which translates into reduced current stock prices (see Pindyck, 1984; French, Schwert and Stambaugh, 1987; and Campbell and Hentschel, 1992); this dampens volatility in the case of good news but exacerbates it in the case of bad news.

As Aït Sahalia, Fan and Li (2013) summarise: "The leverage explanation suggests that a negative return should make the firm more levered, hence riskier and therefore lead to higher volatility; the volatility feedback effect is consistent with the same correlation but reverses the causality: increases in volatility lead to future negative returns." More recently arbitrage restrictions and behavioural explanations have been put forward to explain the asymmetry (for a review; see Talpsepp and Rieger, 2010). In addition, Whitelaw (2000) shows how the Low Risk effect and the volatility-return asymmetry arise in a general equilibrium model with two-regimes as a result of hedging demand. While the jury is still out on the relative contributions of these different explanations (although there is a consensus to recognise that the leverage explanation can only contribute marginally), the phenomenon of negative correlations between volatility and returns itself is not in doubt.

[10] All off-the-shelf multi-strategy indices equally weight the five diversification strategies available from ERI Scientific Beta: Maximum Deconcentration, Diversified Risk Weighted, Maximum Decorrelation, Efficient Minimum Volatility and Efficient Maximum Sharpe Ratio.

Exhibit 3: Smart Factor Index Allocation of the Scientific Beta Multi-Beta Multi-Strategy Relative Volatility (90%) solution (US Long-Term Track Record)

The chart shows the evolution of the allocation across the 30 [6 factors x 5 weightings] Smart Factor Indices for the Scientific Beta US Long-Term Track Record (LTTR) period. The factor tilts are Mid Cap, Value, Positive Momentum, Low Volatility, Low Investment, and High Profitability. The weighting schemes are Maximum Deconcentration, Diversified Risk Weighted, Maximum Decorrelation, Efficient Minimum Volatility, and Efficient Maximum Sharpe Ratio. The allocation is rebalanced quarterly over the period of 43 years (31 December 1972 to 31 December 2015). The benchmark is the capitalisation-weighted portfolio of all stocks in the Scientific Beta US LTTR universe, which consists of the 500 largest US stocks. Scientific Beta US Long Term Smart Factor Indices have a 45-year track record. As the calibration of solutions requires 2 years, all US Long Term Smart Beta solutions have a 43-year track record. Source: www.scientificbeta.com.



Implementing the relative risk approach

The Scientific Beta Multi-Beta Multi-Strategy Relative Volatility (90%) solution dynamically allocates to ERI Scientific Beta Smart Factor Indices on the basis of their evolving risk characteristics in changing markets in an effort to deliver the targeted constant reduction in volatility relative to the market. The solution dynamically allocates to 30 (single-tilt single-weighting-scheme) Smart Factor Indices to create a multi-factor solution that exhibits dissymmetric defensive characteristics. The six rewarded factors that are subject to consensus in the academic literature are Mid Cap, Value, Positive Momentum, Low Volatility, Low Investment, and High Profitability[11]. The weighting schemes are Maximum Deconcentration, Diversified Risk Weighted, Maximum Decorrelation, Efficient Minimum Volatility, and Efficient Maximum Sharpe Ratio. Technically, the solution relies on a Maximum Deconcentration allocation which maximises diversification measured by the effective number of constituent Smart Factor Indices (defined as the inverse of the sum of squared constituent weights: $ENC(w)=1/(w^T*w)$) subject to a constraint of a minimum of 10%[12] *ex-ante* reduction in volatility relative to the reference index. The allocation problem can be written

[11] For more details, please refer to Amenc et al. (2015), Scientific Beta Multi-Strategy Factor Indices: Combining Factor Tilts and Improved Diversification, available at http://docs.scientificbeta.com/Library/External/White_Papers/ERI_Scientific_Beta_Publication_Scientific_Beta_Multi-Strategy_Factor_Indices; and Goltz (2015), Long-Term Rewarded Equity Factors: What Can Investors Learn from Academic Research? P&I EDHEC-Risk Institute Research for Institutional Money Management supplement, available at http://www.edhec-risk.com/about_us/documents/attachments/PI_EDHEC-Risk_Supplement_August_2015.pdf.

[12] This solution, calibrated with a 90% relative volatility budget, is a good compromise over the long term between limiting downside risk and capturing the upside. Naturally, the organisation of the allocation allows this parameter to be changed and it is technically possible to manage a relative constraint budget of 85% or 95%. We consider that this choice can be made in two ways:

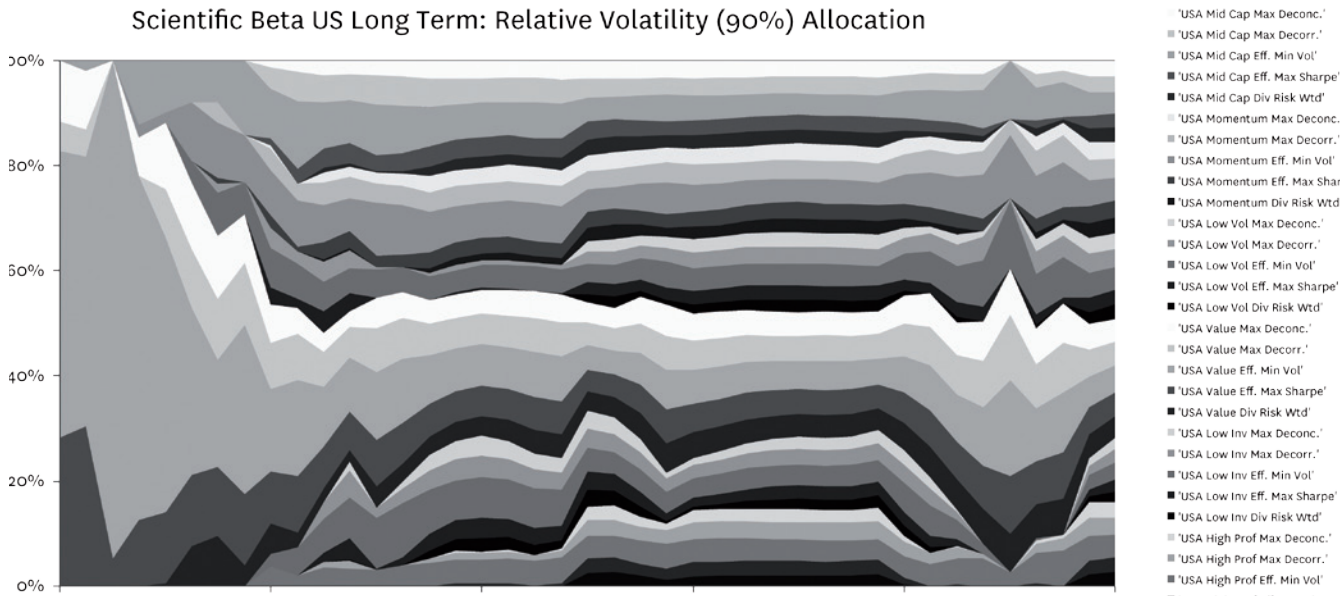
(i) either in a fixed manner: for example the investor would like a more defensive strategy and would choose 85%. This choice has a less optimal long-term trade-off, but it can be taken into account as part of the customisation of our solution's risk budget.

(ii) or in a variable manner, i.e. the investor has views on the future level of volatility or market returns and adapts the risk budget to his/her views. The investor will therefore choose to reduce the constraint (e.g. from 90% to 95%) when s/he estimates that s/he is entering into a bull market regime and conversely, will increase the constraint, (e.g. from 90% to 85%), when s/he estimates that there is a strong likelihood that the markets will fall in the medium term.

Of course, by relying on such forecasts, the investor adds alpha to the strategy; the sign and size of this alpha will depend on forecasting skills.

Exhibit 4: Smart Factor Index Allocation of the Scientific Beta Multi-Beta Multi-Strategy Relative Volatility (90%) solution

The chart shows the evolution of the allocation across the 30 [6 factors x 5 weightings] Smart Factor Indices for the Scientific Beta US Long-Term Track Record (LTTR) period. The factor tilts are Mid Cap, Value, Positive Momentum, Low Volatility, Low Investment, and High Profitability. The weighting schemes are Maximum Deconcentration, Diversified Risk Weighted, Maximum Decorrelation, Efficient Minimum Volatility, and Efficient Maximum Sharpe Ratio. The allocation is rebalanced quarterly over the period of 43 years (31 December 1972 to 31 December 2015). The benchmark is the capitalisation-weighted portfolio of all stocks in the Scientific Beta US LTTR universe, which consists of the 500 largest US stocks. Scientific Beta US Long Term Smart Factor Indices have a 45-year track record. As the calibration of solutions requires 2 years, all US Long Term Smart Beta solutions have a 43-year track record. Source: www.scientificbeta.com.



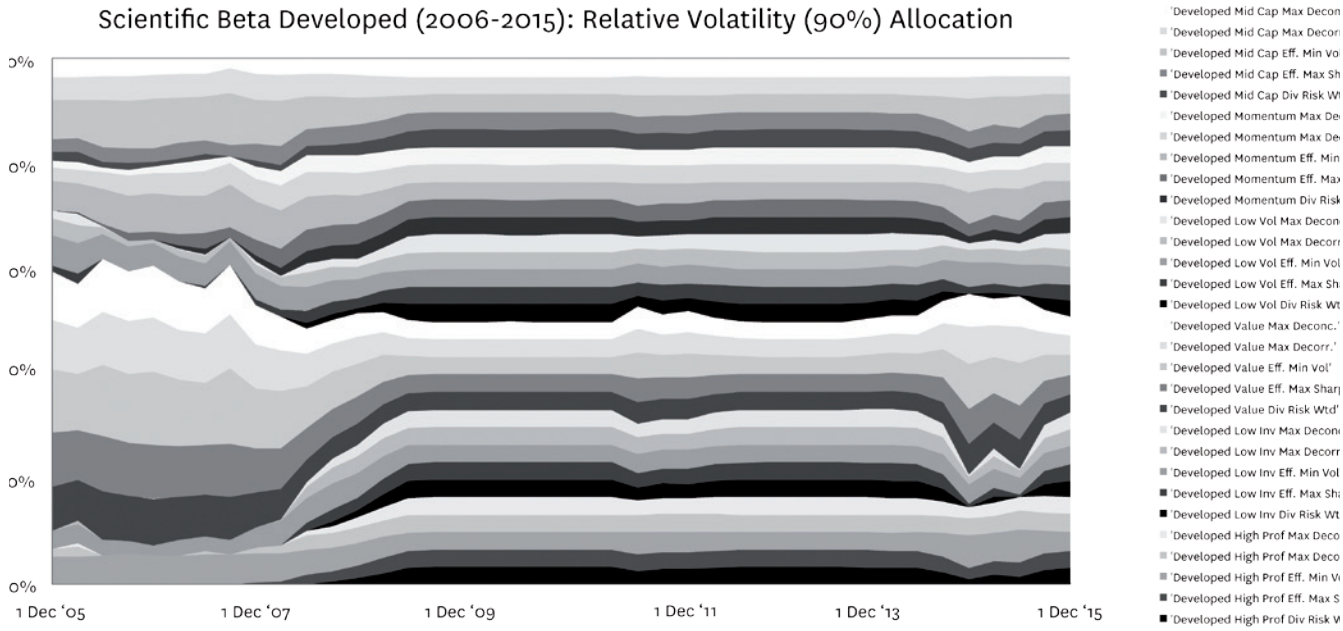


Exhibit 5: Comparison of Solution Concept to Scientific Beta Long-Term Low Volatility Indices

The analysis is based on daily total return data in dollars from December 31, 1972 to December 31, 2015 (43 years). Regressions are performed using weekly total returns in dollars. The Scientific Beta Multi-Beta Multi-Strategy Relative Volatility (90%) allocation is performed using 30 [6 factors x 5 weightings] Smart Factor Indices implemented in the Scientific Beta U.S. Long-Term Track Record (LTTR) universe. The factor tilts are Mid Cap, Value, Positive Momentum, Low Volatility, Low Investment, and High Profitability. The weighting schemes are Maximum Deconcentration, Diversified Risk Weighted, Maximum Decorrelation, Efficient Minimum Volatility, and Efficient Maximum Sharpe Ratio. The allocation is rebalanced quarterly over the period of 43 years (31 December 1972 to 31 December 2015). Scientific Beta US Long Term Smart Factor Indices have a 45-year track record. As the calibration of solutions requires two years, all US Long Term Smart Beta solutions have a 43-year track record. The benchmark is the capitalisation-weighted portfolio of all stocks in the Scientific Beta US LTTR universe, which consists of the 500 largest US stocks. The risk-free rate is the return of the 3-month US Treasury Bill. The Maximum Relative Drawdown is the maximum drawdown of the long-short index, the return of which is given by the fractional change in the ratio of the strategy index to the benchmark index. The 95% Tracking Error is the 95th percentile of 1-year rolling tracking error and is computed using a 1-week step size. The probability of outperformance is the probability of obtaining positive excess returns from investing in the strategy for a period of 1, 3 or 5 years at any point during the history of the strategy using a rolling window and a 1-week step size. Rolling Volatility statistics are reported as mean, standard deviation and 95th percentile of annualised volatility computed using a 3-year rolling window and a 1-week step size. Quarters with positive benchmark index returns are classed as bull quarters and the remaining are classed as bear quarters. The top 25% quarters with the best benchmark index returns are extreme bull quarters and the bottom 25% quarters with the worst benchmark index returns are extreme bear quarters. The returns on the market factor are the returns of the capitalisation-weighted benchmark over the risk-free rate. Reported turnover is 1-way, annual and it is averaged across 172 rebalancings in the 43-year period. Source: www.scientificbeta.com.

31-Dec-1972 to 31-Dec-2015 (43 Years)	Scientific Beta US Broad CW	Scientific Beta Multi-Beta Multi-Strategy Relative Volatility (90%)	Scientific Beta Low Volatility Diversified Multi-Strategy	Scientific Beta Low Volatility Efficient Minimum Volatility
Ann. Returns	10.16%	13.67%	12.94%	13.04%
Ann. Volatility	17.15%	14.64%	14.08%	13.26%
Sharpe Ratio	0.29	0.58	0.56	0.60
Max Drawdown	54.63%	48.70%	48.31%	42.42%
Ann. Rel. Returns	-	3.51%	2.77%	2.88%
Ann. Tracking Error	-	5.13%	6.08%	7.09%
95% Tracking Error	-	8.77%	11.43%	13.96%
Information Ratio	-	0.68	0.46	0.41
Outperf Prob. (1Y)	-	71.26%	66.01%	61.91%
Outperf Prob. (3Y)	-	81.32%	76.53%	75.14%
Outperf Prob. (5Y)	-	88.10%	86.14%	81.05%
Max Relative Drawdown	-	33.18%	43.46%	46.94%
3-Year Rolling Vol Mean	16.40%	13.99%	13.43%	12.70%
3-Year Rolling Vol Std	5.33%	4.61%	4.47%	4.04%
3-Year Rolling Vol 95%	29.29%	25.06%	24.63%	22.11%
Ann. Rel. Returns Bull	-	1.84%	-0.77%	-2.02%
Ann. Rel. Returns Bear	-	5.53%	7.52%	9.64%
Ann. Rel. Returns Extreme Bull	-	-0.69%	-6.39%	-9.62%
Ann. Rel. Returns Extreme Bear	-	5.14%	7.35%	9.74%
CAPM Market Beta	**1.00**	**0.86**	**0.80**	**0.74**
1-Way Turnover	3.1%	39.4%	26.5%	34.6%

'The strategy ... seeks to maximise the diversity of constituent indices'

mathematically as:

$$w^* = argmax\{1/(w^T * w)\} \begin{cases} \sum_{i=1}^{N} w_i = 1 \\ w_i \geq 0 \; \forall \, i \\ \sqrt{W^T * \sum * W} \leq 90\% * Volatility_{CW} \end{cases}$$

w_i represents the weight of the i-th constituent index. N is the number of constituent indices. $\sum$ is the covariance matrix of total returns. Weekly total returns over the previous 104 weeks are used to directly estimate this small (i.e. 30x30) variance-covariance matrix and the volatility of the capitalisation-weighted benchmark. Rebalancing across Smart Factor Indices is implemented quarterly and is not subject to turnover control. This risk-based allocation model exploits the full correlation structure of Smart Factor Indices across the six factor-tilts and five weighting-schemes simultaneously. Relying on the persistent nature of volatility, the adjustment is done strictly on the basis of (*ex-ante*) realised volatility and as such requires no volatility forecasting.

Properties and performance of the relative risk approach

Exhibits 1 and 2 show plots comparing

Exhibit 6: Comparison of Benchmark to Scientific Beta Low Volatility Indices and Traditional Defensive Strategies for the US (2006-2015)

The analysis is based on daily total return data in dollars from 31 December 2005 to 31 December 2015 (10 years). Regressions are performed using weekly total returns in dollars. The Scientific Beta Multi-Beta Multi-Strategy Relative Volatility (90%) allocation is performed using 30 [6 factors x 5 weightings] Smart Factor Indices in the Scientific Beta US universe. The factor tilts are Mid Cap, Value, Positive Momentum, Low Volatility, Low Investment, and High Profitability. The weighting schemes are Maximum Deconcentration, Diversified Risk Weighted, Maximum Decorrelation, Efficient Minimum Volatility, and Efficient Maximum Sharpe Ratio. The allocation is rebalanced quarterly over the period of 10 years (31 December 2005 to 31 December 2015). The benchmark for performing the allocation is the Scientific Beta US capitalisation-weighted index. The benchmark for analytics reporting is the S&P 500 Index. The Scientific Beta US universe consists of the 500 largest US stocks. The risk-free rate is the return of the three-month US Treasury Bill. The 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. The 95% Tracking Error is the 95th percentile of 1-year rolling tracking error and is computed using 1-week step size. The probability of outperformance is the probability of obtaining positive excess returns from investing in the strategy for a period of 1, 3 or 5 years at any point during the history of the strategy using a rolling window and a 1-week step size. Rolling Volatility statistics are reported as mean, standard deviation and 95th percentile of annualised volatility computed using a 3-year rolling window and a 1-week step size. Quarters with positive benchmark index returns are classed as bull quarters and the remaining are classed as bear quarters. The top 25% quarters with the best benchmark index returns are extreme bull quarters and the bottom 25% quarters with the worst benchmark index returns are extreme bear quarters. The returns on the market factor are the returns of the capitalisation-weighted benchmark over the risk-free rate. Reported turnover is one-way annual and it is averaged across 40 rebalancings in the 10-year period. Source: www.scientificbeta.com and Bloomberg.

31-Dec-2005 to 31-Dec-2015 (10 Years)	S&P 500	Scientific Beta Multi-Beta Multi-Strategy Relative Volatility (90%)	Scientific Beta Low Volatility Diversified Multi-Strategy	Scientific Beta Low Volatility Efficient Minimum Volatility	MSCI USA Minimum Volatility	S&P500 Low Volatility
Ann. Returns	7.28%	9.34%	9.62%	10.54%	8.86%	9.35%
Ann. Volatility	20.71%	18.00%	17.25%	15.70%	17.14%	15.28%
Sharpe Ratio	0.30	0.46	0.49	0.60	0.45	0.54
Max Drawdown	55.25%	48.70%	48.31%	42.42%	46.61%	40.40%
Ann. Rel. Returns	-	2.06%	2.34%	3.26%	1.58%	2.07%
Ann. Tracking Error	-	4.37%	5.25%	7.00%	5.32%	8.54%
95% Tracking Error	-	8.99%	9.67%	13.87%	8.39%	17.71%
Information Ratio	-	0.47	0.45	0.47	0.30	0.24
Outperf Prob. (1Y)	-	71.91%	62.55%	65.74%	57.66%	50.21%
Outperf Prob. (3Y)	-	97.27%	91.80%	86.89%	74.86%	69.67%
Outperf Prob. (5Y)	-	100.00%	99.24%	95.04%	79.01%	73.28%
Max Relative Drawdown	-	8.27%	8.79%	12.30%	12.83%	18.75%
3-Year Rolling Vol Mean	21.74%	19.05%	17.91%	16.33%	17.62%	15.76%
3-Year Rolling Vol Std	7.04%	5.62%	6.02%	5.13%	6.47%	4.72%
3-Year Rolling Vol 95%	30.61%	26.08%	25.48%	22.83%	25.79%	21.72%
Ann. Rel. Returns Bull	-	-0.87%	-2.20%	-3.28%	-4.64%	-6.59%
Ann. Rel. Returns Bear	-	5.92%	8.54%	12.49%	10.37%	14.78%
Ann. Rel. Returns Extreme Bull	-	-5.41%	-8.03%	-11.69%	-9.48%	-14.89%
Ann. Rel. Returns Extreme Bear	-	6.09%	9.15%	13.91%	11.97%	16.13%
CAPM Market Beta	**1.00**	**0.87**	**0.82**	**0.74**	**0.80**	**0.68**
1-Way Turnover	NA	41.5%	28.2%	36.0%	NA	NA

the ex-post or out-of-sample volatilities of the broad capitalisation-weighted benchmark and the Scientific Beta Multi-Beta Multi-Strategy Relative Volatility (90%) solution. A 1-year rolling window and 1-week step size is used to plot time-varying volatility. The plots illustrate that the ex-post delivered volatility of the solution is typically very close to the maximum targeted volatility. However, the volatility reduction has been significantly above the minimum targeted level in several periods, typically during bear markets, e.g. 1973-1974 (oil crisis), 2000-2002 (dotcom crash), 2008-2009 (global financial crisis). It has also been so during the bull-run of the late nineties when diversified indices tilted towards long-term rewarded factors could not match the volatility of a cap-weighted index increasingly concentrated into high volatility technology stocks. Undershooting episodes, which should be expected when volatility suddenly rises, have been benign and extremely rare.

Exhibits 3 and 4 below illustrate the dynamic multi-factor nature of the solution. When market volatility is high, delivering a 10% reduction in volatility is a strong constraint that leads the

Exhibit 7: Comparison of Benchmark to Scientific Beta Low Volatility Indices and Traditional Defensive Strategies for Developed Markets (2006-2015)

The analysis is based on daily total return data in dollars from 31 December 2005 to 31 December 2015 (10 years). Regressions are performed using weekly total returns in dollars. The Scientific Beta Multi-Beta Multi-Strategy Relative Volatility (90%) allocation is performed using 30 [six factors x five weightings] Smart Factor Indices in the Scientific Beta US universe. The factor tilts are Mid Cap, Value, Positive Momentum, Low Volatility, Low Investment, and High Profitability. The weighting schemes are Maximum Deconcentration, Diversified Risk Weighted, Maximum Decorrelation, Efficient Minimum Volatility, and Efficient Maximum Sharpe Ratio. The allocation is rebalanced quarterly over the period of 10 years (31 December 2005 to 31 December 2015). The benchmark for performing the allocation is the Scientific Beta Developed capitalisation-weighted index. The benchmark for analytics reporting is the MSCI World Index. The Scientific Beta Developed universe consists of 2,000 large and mid-cap stocks. The risk-free rate is the return of the 3-month US Treasury Bill. The 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. The 95% Tracking Error is the 95th percentile of one-year rolling tracking error and is computed using one-week step size. The probability of outperformance is the probability of obtaining positive excess returns from investing in the strategy for a period of one, three or five years at any point during the history of the strategy using a rolling window and a one-week step size. Rolling Volatility statistics are reported as mean, standard deviation and 95th percentile of annualised volatility computed using a three-year rolling window and a one-week step size. Quarters with positive benchmark index returns are classed as bull quarters and the remaining are classed as bear quarters. The top 25% quarters with the best benchmark index returns are extreme bull quarters and the bottom 25% quarters with the worst benchmark index returns are extreme bear quarters. The returns on the market factor are the returns of the capitalisation-weighted benchmark over the risk-free rate. Reported turnover is one-way, annual and it is averaged across 40 rebalancings in the 10-year period. Source: www.scientificbeta.com and Bloomberg.

31-Dec-2005 to 31-Dec-2015 (10 Years)	MSCI World	Scientific Beta Multi-Beta Multi-Strategy Relative Volatility (90%)	Scientific Beta Low Volatility Diversified Multi-Strategy	Scientific Beta Low Volatility Efficient Minimum Volatility	MSCI World Minimum Volatility	S&P GIVI Developed
Ann. Returns	5.54%	8.23%	8.58%	9.35%	7.30%	6.52%
Ann. Volatility	17.80%	15.25%	13.98%	12.86%	12.81%	15.62%
Sharpe Ratio	0.25	0.47	0.53	0.64	0.48	0.35
Max Drawdown	57.46%	50.86%	49.55%	45.02%	47.35%	53.11%
Ann. Rel. Returns	-	2.69%	3.04%	3.81%	1.76%	0.98%
Ann. Tracking Error	-	3.49%	4.83%	6.19%	6.74%	3.30%
95% Tracking Error	-	7.52%	9.24%	12.29%	10.95%	6.25%
Information Ratio	-	0.77	0.63	0.62	0.26	0.30
Outperf Prob. (1Y)	-	81.06%	65.53%	68.09%	56.60%	56.81%
Outperf Prob. (3Y)	-	99.18%	96.99%	93.17%	74.59%	87.16%
Outperf Prob. (5Y)	-	100.00%	100.00%	97.33%	79.01%	94.27%
Max Relative Drawdown	-	7.72%	9.76%	13.43%	17.42%	5.75%
3-Year Rolling Vol Mean	18.92%	16.29%	14.73%	13.53%	13.27%	16.51%
3-Year Rolling Vol Std	5.32%	4.12%	4.16%	3.68%	4.44%	4.76%
3-Year Rolling Vol 95%	25.44%	21.23%	19.82%	18.07%	18.82%	22.33%
Ann. Rel. Returns Bull	-	0.49%	-1.28%	-2.41%	-6.16%	-1.49%
Ann. Rel. Returns Bear	-	5.32%	8.58%	12.08%	12.73%	4.10%
Ann. Rel. Returns Extreme Bull	-	-2.44%	-7.74%	-11.54%	-13.99%	-4.10%
Ann. Rel. Returns Extreme Bear	-	6.03%	10.05%	14.09%	14.72%	4.38%
CAPM Market Beta	**1.00**	**0.86**	**0.78**	**0.71**	**0.69**	**0.88**
1-Way Turnover	NA	35.0%	29.5%	36.4%	NA	NA

risk-based allocation to concentrate into the most defensive Smart Factor Indices in the available pool; these defensive indices will outperform in bear markets and thus incur well-rewarded tracking error relative to the broad-market benchmark. When market volatility is low, the volatility reduction constraint is less strong and allows allocation to be broadly diversified across the Smart Factor Indices in the available pool. Note that when the constraint is not binding, the allocation model achieves equal-weighting across all available indices. In these market conditions, the solution will rely more on indices exhibiting good bull-market performance and will not be primarily invested in defensive indices that incur high detrimental tracking error because of their inferior bull-market performance.

For the above reasons, the tracking error of the solution will also be dissymmetric. The highly defensive indices in which the solution concentrates in high-volatility regimes will outperform in bear markets and thus incur well-rewarded tracking error relative to the broad-market benchmark. The mildly defensive character of the

'The most important value added of this solution, is its ability to combine significant downside protection and excellent upside capture'

solution in low volatility environments will reduce the traditional performance drag and associated high tracking error of unconditional defensive approaches in bull markets and the broad mix of indices to which the solution allocates in these environments will harvest multiple sources of factor returns that will further improve relative performance. In other words, the solution should exhibit high bear-market tracking error corresponding to outperformance being created by the marked defensive character of the allocation and more benign bull-market tracking error reflecting a muted defensive character that allows for harvesting multiple risk premia and at least avoiding severe underperformance.

Naturally, the Smart Factor Index diversification objective and relative risk budget approach of the strategy's allocation mechanism also allow investors to avoid the factor concentration issue of traditional defensive strategies. The strategy indeed draws on six systematic sources of long-term over-performance relative to the broad equity markets by tilting towards Mid Cap, Value, Positive Momentum, Low Volatility, Low Investment and High Profitability stocks. In allocating to indices representative of these tilts, the strategy does not attempt to time factor cycles but instead seeks to maximise the diversity of constituent indices, subject to the volatility budget.

As shown in Exhibit 5, over the very long-term (43-year record), the Scientific Beta U.S. Long-Term Multi-Beta Multi-Strategy Relative Volatility (90%) solution respects its constraint of a minimum volatility reduction of 10% – it achieves a robust 15% reduction – and produces higher returns than the Low Volatility Smart Factor Indices. Its Sharpe ratio is twice that of the benchmark, on par with that of the two Low Volatility indices. The solution's high outperformance of 3.51% p.a. and lower tracking error – a result of its dissymmetric defensive profile and the exploitation of decorrelation opportunities across both the factor and weighting scheme dimensions – combine to produce an information ratio of 0.68, which is exceptionally high for a defensive strategy.

The most striking observation, which is also the most important value added of this solution, is its ability to combine significant downside protection and excellent upside capture. Due to its dynamic character, the strategy gears downs its defensive exposure in low volatility environments and outperforms by 1.84% in bull markets over the period when even well-diversified defensive strategies underperform. The benefits of dynamic allocation are even more evident in extreme bull markets: the strategy trails by a mere 69bps, when the Low Volatility Multi-Strategy Index is 639bps behind the benchmark and the Low Volatility Efficient Minimum Volatility Index underperforms by 962bps. Relative to these indices, the strategy shows higher probabilities of outperformance in the short and medium term and a lower maximum relative drawdown.

In summary, the Scientific Beta Multi-Beta Multi-Strategy Relative Volatility (90%) solution comes across as an excellent compromise between performance and downside protection. It provides about the same reduction in volatility as the Scientific Beta Low Volatility Diversified Multi-Strategy index, but a much higher information ratio and a much better upside capture. This translates into greater robustness of outperformance across time and states as illustrated by the solution's superior probabilities of outperformance.

Exhibit 6 shows that the performance of the Scientific Beta U.S Multi-Beta Multi-Strategy Relative Volatility (90%) solution over the last 10 years is consistent with the long-term track record. The reduction in volatility of this solution over the 10-year period is 13%, which respects the constraint, and it displays the same ability to provide both significant downside protection and excellent upside capture. Relative to the ERI Scientific Beta Low Volatility indices and third-party defensive strategies, the strategy shows lower tracking error and boasts the best information ratio; it has higher probabilities of outperformance in the short and medium term and a lower relative drawdown. In a decade that has been particularly beneficial to highly defensive strategies, the benchmark delivers the same excess performance, about 2% p.a., as the most defensive product on the market with twice its information ratio and vastly higher probabilities of outperformance over the short and medium term.

Exhibit 7 shows performance comparisons over the same period for developed markets as a whole. The reduction in volatility of the Scientific Beta Multi-Beta Multi-Strategy Relative Volatility (90%) solution over the 10-year period is 14% and the benchmark displays the same ability to provide both significant downside protection and excellent upside capture. Relative to the ERI Scientific Beta Low Volatility indices and more defensive third-party strategies, the strategy shows lower tracking error and a lower relative drawdown. While

'The [approach] avoids the factor concentration issue of traditional defensive strategies'

it is dominated by the ERI Scientific Beta Low Volatility indices in terms of returns and Sharpe ratio, due to a market environment that favoured defensive strategies, it delivers a much higher information ratio and has much higher probabilities of outperformance in the short and medium term.

De facto, the Scientific Beta Multi-Beta Multi-Strategy Relative Volatility (90%) solution represents a solution that is very different from the defensive strategies proposed by the Scientific Beta Low Volatility Diversified Multi-Strategy or Scientific Beta Low Volatility Efficient Minimum Volatility indices. It no longer involves offering a defensive strategy that performs as well as possible in bear market situations (Scientific Beta Low Volatility Efficient Minimum Volatility), because it has a very low beta, but is well diversified; nor does it involve focusing on the capture of the risk premium associated with the Low Risk factor as efficiently as possible (Scientific Beta Low Volatility Multi-Strategy) by making sure to obtain excellent risk-adjusted performance through good diversification (i.e. reduction) of weighting scheme idiosyncrasies.

The solution does not involve being concentrated in the Low Volatility factor, but allocating to the six rewarded factors that are subject to consensus in the academic literature. It is the dynamic nature of the multi-index allocation that will allow the strategy to be most defensive when most useful, i.e. when the markets are highly volatile. The investor will ultimately avail of a dissymmetric pay-off that has the advantages of a defensive strategy as it protects against downside risk and outperforms the capitalisation-weighted benchmark strongly in bear and extreme bear markets, but does not present the disadvantage of traditional defensive strategies which underperform in bull markets. Better upside capture is produced by good factor diversification that is made possible by a lower absolute volatility reduction constraint during low volatility periods that generally correspond to periods of market rises.

Conclusion

Implemented in a long-only and unleveraged framework, the ERI Scientific Beta Smart Factor Indices that tilt towards Low Volatility stocks acquire a defensive character, which can be maximised by selection of the Efficient Minimum Volatility weighting scheme. Relative to equally defensive solutions put forward by other providers, the superior diversification of the ERI Scientific Beta Low Volatility indices produces significantly higher returns, adjusted returns and probabilities of outperformance. However, these defensive solutions are concentrated on the Low Risk factor and thus miss out on the rewards associated with other factor tilts. Also, their unconditional defensive character, i.e. a constantly low beta, causes them to significantly trail the benchmark in strong bull markets.

To address these issues, the Scientific Beta Multi-Beta Multi-Strategy Relative Volatility (90%) solutions rely on risk-based allocation models engineered by EDHEC-Risk Institute to select and dynamically allocate to the whole gamut of ERI Scientific Beta Smart Factor Indices carrying long-term risk premia to deliver a dissymmetric defensive profile. Relying on the persistence of volatility and the negative relationship between volatility and returns, these benchmarks target a constant reduction in relative volatility vis-à-vis the broad market capitalisation-weighted index that allows the defensive character of the strategy to adjust to market conditions and combine downside risk protection with improved upside capture. Compared to unconditional defensive strategies, they exhibit excellent upside capture, exceptional information ratios and much higher probabilities of outperformance in the short and medium term. As such, these benchmarks constitute in our view core solutions for buy-and-hold investors who seek a defensive allocation but wish to reduce the risk of short and/or medium term underperformance relative to a peer group or the broad-market capitalisation-weighted index.

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Evaluating the live performance of multi smart factor indices

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Introduction

This article discusses the live performance of stock market indices that aim to outperform cap-weighted indices by obtaining exposure to multiple rewarded factors and by using diversification-based weighting schemes – so-called smart factor indices. Given the potential data-mining biases that can arise when relying on backtested performance, a key issue when analysing such multi-factor indices is to look at their live performance, which does not benefit from hindsight in the way that back-tests potentially can. In the end, the key question for investors is not backtested performance, but the live performances they will ultimately experience when adopting such indices.

In particular, we discuss Multi-Beta Multi-Strategy indices that allocate across several smart factor indices. One such strategy is the Scientific Beta Multi-Beta Multi-Strategy Four-Factor EW index, whose live performance is the longest among the live performances of the Scientific Beta offerings and is therefore the central topic of the following pages.

This flagship index is an equal-weighted combination of four underlying single-factor indices, for the Mid-Cap, Momentum, Low-Volatility and Value factors respectively. Equal-weighting the underlying single factor indices is a straightforward way of performing a multi-factor allocation. This approach thus uses individual smart factor indices as the principal ingredients. Hence, their good design is a necessary condition for the flagship multi-factor index to work seamlessly.

The single factor indices serve as efficient and well-diversified building blocks for multi-factor allocations due to their parsimonious methodology. Academic consensus and concern for robustness underlie the design of all Scientific Beta indices. First and foremost, the single factor indices are based on the idea of diversification. Diversification is the only "free lunch" available in investment management and investors ignore it at their peril.

ERI Scientific Beta, with its Smart Beta 2.0 approach, enables investors to obtain the right rewarded risk factor exposures in an efficient and well-diversified way. The main idea is to apply a smart weighting scheme to an explicit selection of stocks in order to construct factor indices that 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: 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.

The smart weighting used in the four underlying indices behind the Scientific Beta Multi-Beta Multi-Strategy EW index is called Diversified Multi-Strategy. This weighting scheme combines five popular weighting schemes and thus diversifies the specific risks of the individual weighting approaches.

There is strong intuition suggesting that multi-factor allocations will tend to result in improved risk-adjusted performance. In fact, even though the factors towards which the factor indices are tilted are all rewarded over the long term, there is extensive evidence that they may each encounter prolonged periods of underperformance. One can expect pronounced allocation benefits across factors which have imperfect correlation with one another. This is the reason why multi-factor allocation can add value for investors.

The Scientific Beta Multi-Beta Multi-Strategy Four-Factor EW index is designed to add value in this way. Launched in December 2013, its live performance is testimony to the robust methodology employed by Scientific Beta in its indices. The following sections present this multi-factor index in more detail, mostly focusing on the performance since launch.

A First Look at Live Performance

Prior to discussing the performance of the flagship multi-factor index, we take a look at the live results of the single factor indices that constitute the Scientific Beta Multi-Beta Multi-Strategy Four-Factor EW index.

The Scientific Beta Multi-Strategy indices for the Mid-Cap, Momentum, Low-Volatility and Value factors were launched in December 2012 and during their live period have outperformed the cap-weighted index while reducing

[13] The Efficient Maximum Sharpe Ratio, Efficient Minimum Volatility, Maximum Deconcentration, Diversified Risk Weighted and Maximum Decorrelation weighting schemes. More details available at www.scientificbeta.com.

Exhibit 1: Performance and Risks of Single Factor Indices – Live Period– Developed Region

Statistics are annualised and daily total returns from 21/12/2012 to 30/06/2016 are used for the analysis. The Scientific Beta Developed CW index is used as the cap-weighted benchmark. The yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. Source: www.scientificbeta.com.

Performance and Risks Developed Region (21/12/2012 - 30/06/2016)	Scientific Beta Multi-Strategy Indices				Average of the 4 Single-Factor Indices
	Mid-Cap	Momentum	Low-Volatility	Value	
Change in volatility w.r.t. CW benchmark	-0.61%	-0.58%	-1.86%	-0.09%	-0.78%
Relative change in volatility w.r.t. CW benchmark	-5.25%	-4.98%	-16.11%	-0.79%	-6.78%
Annualised Excess Returns	2.31%	2.96%	3.83%	0.83%	2.48%
Annualised Tracking Error	2.58%	2.71%	3.17%	1.99%	2.61%
Information Ratio	0.90	1.09	1.21	0.42	0.90

Exhibit 2: Performance and Risks of Multi Factor Indices – Live Period – Different Geographical Regions

Statistics are annualised and daily total returns from 20/12/2013 to 30/06/2016 are used for the analysis. The Scientific Beta CW index in the corresponding regions is used as the cap-weighted benchmark. The yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate with the exception of the Eurozone, United Kingdom and Japan where Euribor (3M), UK T-bill (3M) and Japan Gensaki T-bill (1M) are used respectively. Source: www.scientificbeta.com.

Performance and Risks - Live Period Different Geographical Regions (20/12/2013 - 30/06/2016)	Scientific Beta Multi-Beta Multi-Strategy Four-Factor EW index						
	Annualised Returns	Annualised Volatility	Change in Volatility w.r.t. CW Benchmark	Relative Change in Volatility w.r.t. CW Benchmark	Annualised Excess Returns	Annualised Tracking Error	Information Ratio
United States	9.95%	13.19%	-0.82%	-5.87%	2.14%	2.53%	0.85
Eurozone	7.25%	17.63%	-2.72%	-13.38%	4.08%	4.77%	0.85
United Kingdom	5.77%	15.32%	-0.54%	-3.43%	2.62%	4.90%	0.54
Developed Europe ex-UK	0.62%	16.43%	-1.51%	-8.40%	3.79%	3.96%	0.96
Japan	8.87%	19.90%	-2.42%	-10.85%	7.71%	4.90%	1.57
Developed Asia-Pacific ex-Japan	1.48%	11.78%	-3.56%	-23.20%	4.21%	5.76%	0.73
Developed ex-UK	7.17%	10.86%	-1.06%	-8.87%	3.38%	2.15%	1.57
Developed ex-USA	2.32%	12.54%	-1.42%	-10.19%	4.56%	2.86%	1.60
Developed	6.44%	11.13%	-1.03%	-8.50%	3.31%	2.13%	1.55
Average across regions	5.54%	14.31%	-1.68%	-10.30%	3.98%	3.77%	1.14

volatility. For example, the average annualised outperformance of the four indices in the Developed region, shown in above, was 2.48%. The average reduction in volatility compared to the reference index amounted to 78 basis points in absolute terms, which is 6.78% in relative terms. The indices also delivered low tracking error, which led to a rather high average information ratio of 0.9. It should be noted that, despite a relatively tough time for Value strategies over this period, the Scientific Beta Developed Value Multi-Strategy Index managed to outperform the cap-weighted reference index, as shown in Exhibit 1. In the end, it is the good diversification of this index which has produced this good performance, even though the cap-weighted Value index drawing on the same stock selection has actually underperformed the broad cap-weighted index over this period.

The benefits of good design and the resulting good performance of the constituent indices carry over to the flagship multi-factor index. The Scientific Beta Multi-Beta Multi-Strategy Four-Factor EW index is an example of simple and robust allocation to smart factors. This index draws on the good live performance of the underlying indices and we can thus expect benefits from this multi-beta allocation, in line with the averages from the exhibit above.

In Exhibit 2 we show the live performance of the Scientific Beta Multi-Beta Multi-Strategy Four-Factor EW index starting with its official launch in December 2013. In each geographical universe we compare the regional version of this flagship index with its corresponding Scientific Beta Cap-Weighted index. An important take-away from the exhibit is the consistency of the key results across different geographical regions and the alignment of the results with the observed behaviour of the single-factor indices. The multi-factor index outperformed the cap-weighted index in all the regions with an average

Exhibit 3: Yearly Performance of Multi Factor Indices – Live Period – Different Geographical Regions

Yearly non-annualised excess returns for the live period of the Scientific Beta Multi-Beta Multi-Strategy 4 Factor EW index are shown. 2016 YTD Performance refers to the period between 31/12/2015 and 30/06/2016. The Scientific Beta CW index in the corresponding regions is used as the cap-weighted benchmark. The yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate with the exception of the Eurozone, United Kingdom and Japan where Euribor (3M), UK T-bill (3M) and Japan Gensaki T-bill (1M) are used respectively. Source: www.scientificbeta.com.

Live Excess Returns (Yearly) Different Geographical Regions	Scientific Beta Multi-Beta Multi-Strategy Four-Factor EW index		
	2014	2015	2016 YTD
United States	2.39%	0.49%	2.83%
Eurozone	3.15%	5.89%	1.73%
United Kingdom	6.03%	7.23%	-6.68%
Developed Europe ex-UK	2.21%	4.63%	2.92%
Japan	6.31%	6.82%	5.81%
Developed Asia-Pacific ex-Japan	2.44%	5.07%	2.45%
Developed ex-UK	2.93%	2.32%	3.35%
Developed ex-USA	3.71%	5.35%	2.43%
Developed	3.08%	2.68%	2.65%
Average across regions	3.58%	4.49%	1.94%

Exhibit 4: Performance and Risks – Scientific Beta Multi-Beta Multi-Strategy Four-Factor EW Index - US Long Term Track Records

Statistics are annualised and daily total returns from 31/12/1970 to 31/12/2015 are used for the analysis. The Scientific Beta USA LTTR CW index is used as the cap-weighted benchmark. The yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. Source: www.scientificbeta.com.

Performance and Risks - USA Long Term Track Records	Equity Exposure
Change in Volatility w.r.t. CW Benchmark	-1.77%
Relative Change in Volatility w.r.t. CW Benchmark	-10.49%
Annualised Excess Returns	3.35%
Annualised Tracking Error	5.03%
Information Ratio	0.67

Exhibit 5: Performance and Risks – Scientific Beta Multi-Beta Multi-Strategy Four-Factor EW Index - US Long Term Track Records

Statistics are annualised and daily total returns from 31/12/1970 to 31/12/2015 are used for the analysis. The Scientific Beta USA LTTR CW index is used as the cap-weighted benchmark. The yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. Source: www.scientificbeta.com.

Performance and Turnover - Live Period Developed Region (20/12/2013 - 30/06/2016)	Average of 4 Single Factor Indices	Scientific Beta Multi-Beta Multi-Strategy Four-Factor EW index
Annualised Excess Returns	3.29%	3.31%
Annualised Tracking Error	2.74%	2.13%
Information Ratio	1.13	1.55
95th percentile of Rolling 1Y Tracking Error	3.18%	2.60%
Average Ann. 1-Way Turnover	43.32%	37.49%

annualised outperformance of 3.98%. The volatility reduction effects observed among the single-factor indices are present in the multi-factor index as well. Across the different geographies, the four-factor multi-beta index lowered the volatility of the reference cap-weighted index by an average of 1.68%. This represents a 10.30% relative drop in volatility.

Consistency of Live Performance over Time

As we have seen, the live performance of Scientific Beta Multi-Beta Multi-Strategy Four-Factor EW index has

Exhibit 6: Excess Returns of Single Factor Indices – Live Period of Scientific Beta Multi-Beta Multi-Strategy EW Index – Developed Region:

Statistics are annualised and daily total returns from 20/12/2013 to 30/06/2016 are used for the analysis. The Scientific Beta Developed CW index is used as the cap-weighted benchmark. Source: www.scientificbeta.com.

Annualised Excess Returns of Scientific Beta Single Factor Indices Developed Region (20/12/2013 - 30/06/2016)				
	Factor Tilt			
Weighting Scheme	Mid-Cap	Momentum	Low-Volatility	Value
Maximum Deconcentration	1.63%	1.51%	5.35%	-0.73%
Maximum Decorrelation	1.91%	2.81%	5.71%	0.76%
Efficient Minimum Volatility	5.67%	5.39%	7.58%	3.46%
Efficient Maximum Sharpe Ratio	3.15%	3.69%	5.68%	1.77%
Diversified Risk Weighted	2.66%	2.14%	5.50%	0.29%

Exhibit 7: Yearly Performance of Single Factor Indices (Excess Returns) - Developed Region

The table shows the single factor indices with the highest (winner) and lowest (loser) yearly excess return among the 20 (4x5) single factor indices for the Mid-Cap, Momentum, Low-Volatility and Value tilts combined with 5 weighting schemes - Maximum Deconcentration, Maximum Decorrelation, Efficient Minimum Volatility, Efficient Maximum Sharpe Ratio, Diversified Risk Weighted. The table also contains the excess return of the Scientific Beta Multi-Beta Multi-Strategy EW index. 2016 YTD Performance refers to the period between 31/12/2015 and 30/06/2016. The Scientific Beta Developed CW index is used as the cap-weighted benchmark. Source: www.scientificbeta.com.

Scientific Beta Index Name and Excess Return					
	Winner		Loser		Multi-Beta Multi-Strategy Four- Factor EW index
2016 YTD	Low-Volatility Efficient Min.Volatility	6.57%	Momentum Max. Deconcentration	-0.08%	2.65%
2015	Momentum Efficient Max. Sharpe	5.78%	Value Max. Deconcentration	-2.31%	2.68%
2014	Low-Volatility Efficient Min. Volatility	7.23%	Momentum Max. Deconcentration	-0.47%	3.08%
2013	Momentum Max. Deconcentration	4.46%	Low-Volatility Efficient Min. Volatility	-4.12%	0.05%
2012	Value Max. Decorrelation	1.16%	Momentum Efficient Min.Volatility	-2.00%	0.11%
2011	Low-Volatility Efficient Min. Volatility	10.75%	Value Max. Deconcentration	-4.17%	2.91%
2010	Mid-Cap Max. Deconcentration	10.65%	Value Efficient Min. Volatility	2.02%	5.89%
2009	Value Max. Deconcentration	4.91%	Momentum Efficient Min.Volatility	-8.82%	-1.96%
2008	Low-Volatility Efficient Min. Volatility	12.19%	Momentum Max. Deconcentration	-2.79%	2.97%
2007	Momentum Max. Deconcentration	0.58%	Low-Volatility Max. Deconcentration	-5.85%	-3.00%

shown consistent results across the regions. It is only natural to examine the consistency of the returns over time. In the investment management industry, strategies are often assessed on the basis of short-term performance, such as calendar years. The Scientific Beta indices are built around the idea of long-term rewarded factors that might not necessarily work all the time. The multi-factor allocation tries to alleviate this problem and smooth factor cyclicality. Nevertheless, it is still an alternative strategy that will deviate from the cap-weighted reference in any given time period.

The live period of the flagship multi-factor index examined above is more than two and a half years. Examining the entire live period may hide how the strategy performed on a calendar-year basis. Therefore, in Exhibit 3, we show the yearly live excess returns of the index along with the June 2016 year-to-date results. We can observe remarkable stability in the outperformance across regions and time-periods. Indeed, there is only one region/period combination with negative excess return.

Consistency with Long-Term Track Records

The live results presented in this article are a result of constructing factor indices based on the idea of long-term rewards associated with factor exposure.

Exhibit 8: Performance and Risks – Live Period of the Scientific Beta Multi-Beta Multi-Strategy EW Index – Developed Region

Statistics are annualised and daily total returns from 20/12/2013 to 30/06/2016 are used for the analysis. The Scientific Beta Developed CW index is used as the cap-weighted benchmark. The yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. Bull (bear) market performance is calculated based on the quarterly classification of the cap-weighted reference index - calendar quarters with positive benchmark returns comprise bull markets and the rest constitute bear markets. Similarly, extreme bull (bear) markets correspond to quarters with the top (bottom) 25% benchmark returns. The extreme percentile of Tracking Error is calculated using weekly time steps and 1-year rolling window. The performance of the Scientific Beta Multi-Beta Multi-Strategy 6 Factor EW index comes partially from the historical backtrack (prior to 18/09/2015). Source: www.scientificbeta.com.

Performance and Risks - Live Period Developed Region (20/12/2013 - 30/06/2016)	Scientific Beta Multi-Beta Multi-Strategy Four-Factor EW index	Scientific Beta Multi-Beta Multi-Strategy Six-Factor EW index
Annualised Returns	6.44%	6.51%
Annualised Volatility	11.13%	11.18%
Change in Volatility w.r.t. CW Benchmark	-1.03%	-0.98%
Relative change in Volatility w.r.t. CW Benchmark	-8.50%	-8.07%
Sharpe Ratio	0.57	0.57
Annualised Excess Returns	3.31%	3.38%
Annualised Tracking Error	2.13%	1.98%
Information Ratio	1.55	1.70
95th Percentile of Rolling 1Y Tracking Error	2.60%	2.44%
Bull Markets		
Annualised Excess Returns	2.66%	2.68%
Annualised Tracking Error	2.04%	1.90%
Information Ratio	1.30	1.41
Bear Markets		
Annualised Excess Returns	4.62%	4.77%
Annualised Tracking Error	2.34%	2.19%
Information Ratio	1.98	2.18
Extreme Bull markets		
Annualised Excess Returns	0.27%	0.49%
Annualised Tracking Error	2.72%	2.51%
Information Ratio	0.13	0.26
Extreme Bear markets		
Annualised Excess Returns	2.89%	2.91%
Annualised Tracking Error	2.01%	1.84%
Information Ratio	1.44	1.59

Therefore, any factor or multi-factor index should be ultimately linked to the documented historical performance.

In Exhibit 4 we show that the short-term live results presented thus far are consistent with the results from the USA Long-Term Track Records that extend 45 years back in time. Namely, the Scientific Beta Multi-Beta Multi-Strategy Four-Factor EW index from the USA long-term history outperformed the cap-weighted benchmark with an annualised excess return of 3.35%, which compares to the 3.98% seen in the live period across regions. Similarly, the average relative reduction in volatility of 10.49% observed over the long history compares to the regional average of 10.30% from the live period.

Benefits of Multi-Beta Multi-Strategy Allocation

There is more to multi-factor allocation than meets the eye. We have seen that there is a rationale behind combining the single-factor indices, since the average of the four performance metrics naturally avoids extreme values. This intuition materialises in the actual multi-factor EW index, whose live performance preserves the all-important positive excess returns and volatility reduction.

There is an additional benefit to combining the single factor indices into one multi-factor strategy – reduction in turnover. This reduction in turnover arises from the netting of offsetting trades required to rebalance the dollar weights of the same stocks in different constituent indices. Some of these trades are related to a stock entering or exiting the selection from which a Smart Factor Index is built and it can naturally happen that a stock exits one index at the exact same time that it enters another index.

Exhibit 5 documents a difference of nearly 6% between the average turnover of the four underlying single-factor indices and the turnover of the multi-factor index in the Developed region during the live period of the

Exhibit 9: Yearly Performance of Single Factor Multi-Strategy Indices – Live Period of Scientific Beta Multi-Beta Multi-Strategy EW index – Developed Region

This table shows the yearly excess returns of six Scientific Beta single-factor Multi-Strategy indices that constitute the Six-Factor Multi-Beta Multi-Strategy EW index. Yearly non-annualised excess returns for the live period of the Scientific Beta Multi-Beta Multi-Strategy 4 Factor EW index are shown. 2016 YTD Performance refers to the period between 31/12/2015 and 30/06/2016. The Scientific Beta CW index is used as the cap-weighted benchmark. The yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. Source: www.scientificbeta.com.

Excess Returns (Yearly) Developed Region	Scientific Beta Multi-Strategy Indices		
	2014	2015	2016 YTD
Mid-Cap	3.17%	2.61%	1.91%
Momentum	1.23%	4.97%	1.58%
Low Volatility	5.81%	4.26%	5.11%
Value	2.11%	-1.10%	1.91%
High Profitability	4.18%	4.37%	2.31%
Low Investment	2.59%	1.79%	2.43%

strategy (December 2013 to June 2016). In addition to the reduced turnover, the multi-factor index improved the information ratio from 1.13 to 1.55 by reducing the average tracking error. This is accompanied by a reduction in the extreme (95th) percentile of rolling one-year tracking error.

Another important aspect of the multi-beta multi-strategy allocation is avoiding the risks of selecting individual factors or weighting schemes. The multi-factor indices represent passive investment products that do not try to predict the winning strategy or factor, bearing in mind that the rewarded factors yield positive premia in the long term in exchange for risks that can lead to considerable underperformance or relative drawdowns in shorter periods.

In essence, multi-beta multi-strategy indices represent an agnostic view on the capacity to select the winner beforehand. Diversifying across the factors also avoids factor timing and thus avoids both performance chasing and contrarian investing. Indeed, it is important to realise how crucial diversification is. Without the benefits of a crystal ball and after taking into account the large body of evidence that seems to suggest the lack of forecasting skills among the majority of investment professionals, avoiding the risks of being stuck with the wrong strategy seems like a good idea *ex-ante*.

To illustrate this point, let us recall that the Scientific Beta Multi-Beta Multi-Strategy Four-Factor EW index is a combination of four single-factor indices, all of which employ a diversification weighting scheme based on five different approaches. We can examine the difference in performance among the 20 (4x5) alternative strategies that combine one of the four factor tilts and a unique weighting scheme. We present the annualised excess returns of these strategies in Exhibit 6.

During the more than two and a half years-long live period of the flagship multi-factor index, the variation in outperformance among the 20 examined strategies is substantial. The worst-performing strategy turned out to be a Value-tilted index using the Maximum Deconcentration weighting scheme, with an annualised excess return of -0.73%, while the best-performing strategy was a combination of Low-Volatility tilt and Efficient Minimum Volatility weighting scheme, with annualised outperformance of 7.58%.

This wide spread simply means that defensive strategies worked remarkably well in this time period, while Value stocks underperformed. Naturally, investors that had invested in Low Volatility strategies can now be happier than Value investors seeking stock-level diversification through the Value Maximum Deconcentration strategy. This is however an ex-post analysis of a given realisation of stock returns. Other time periods would have produced different results.

With the help of the above example, it can be further shown how the performance of individual strategies can be "rationalised." For instance, a provider of a single strategy similar to Value Maximum Deconcentration would likely seek to sell the idea that the strategy with the lowest recent returns is likely to make a comeback. On the other hand, a provider of a single strategy similar to Low-Volatility Efficient Minimum Volatility would likely emphasise his good performance over the recent patch of rough markets. The Multi-Beta Multi-Strategy index approach is immune to such strategy picking questions and just delivers the "average" result across factors and weighting schemes.

To further illustrate the variability among the many individual strategies that an investor can choose from, consider Exhibit 7, which shows the yearly excess returns[14] of the Scientific Beta Multi-Beta Multi-Strategy Four-Factor EW index in the Developed region along with the yearly excess returns of the worst (losing) and best (winning) performing single factor index among the 20 candidate strategies introduced earlier.

The exhibit shows that every year, the winner and loser would be a different single factor strategy. The Multi-Beta Multi-Strategy index takes no view of the winning strategy or factor and thus can avoid a good share of the uncertainty linked to individual strategies.

The Effect of Adding Quality Factors

Apart from the Mid-Cap, Momentum, Low-Volatility and Value factors and the associated single factor indices, Scientific Beta introduced the High-Profitability and Low-Investment factors into its arrays of single factor indices in March 2015. The two factors represent the quality aspects of the stocks. These six factors have all been combined into a

[14] Results prior to the live date come from an historical backtrack.

'Smart beta at the outset has the potential to provide access to evidence-based long-term investment strategies'

new multi-factor index, the Scientific Beta Multi-Beta Multi-Strategy Six-Factor EW index, which was launched in September 2015.

Exhibit 8 shows the performance comparison between the Scientific Beta Multi-Beta Multi-Strategy Four-Factor and Six-Factor EW indices, along with analysis of conditional performance depending on the market conditions. The bull (bear) markets correspond to analysis of performance of the indices in quarters when the cap-weighted benchmark returns are positive (negative). Similarly, the extreme bull (bear) markets correspond to the quarters with the top (bottom) 25% benchmark returns. This allows the performance to be assessed in different market cycles.

Comparing the results of the four and six-factor indices, we learn that the addition of the new quality factors yielded similar levels of excess returns and slightly lower tracking error. This is also true in the case of the 95th percentile of the rolling one-year tracking error.

The results in the exhibit above also show that the Six-Factor EW index not only exhibits lower tracking error compared to the Four-Factor EW index, while experiencing a similar level of volatility, but the tracking error is also lower across different market regimes, suggesting smoother performance compared to the Four-Factor EW index. This is an important insight since investors not only care about the performance over the entire period, but are also concerned about the relative performance in bull and bear markets.

The performance of the six factor EW index can be traced back to the performance of the underlying six single-factor indices. Exhibit 9 shows the yearly performances of six single-factor multi-strategy indices that serve as building blocks for the Scientific Beta Multi-Beta Multi-Strategy Six-Factor EW index, over the same period as discussed above. It contains the excess returns of these indices over the cap-weighted benchmark in the Developed region.

The single-factor indices based on High Profitability and Low Investment represent two additional sources of performance that help smooth the returns of the multi-factor index. For example, as shown below, High Profitability experienced comparably high excess returns in recent years while Low Investment also added to the good overall results of the multi-factor index with its positive yearly excess returns.

Conclusion

In this article we have focused on the analysis of the Scientific Beta Multi-Beta Multi-Strategy Four-Factor EW index and presented its performance since its launch in December 2013.

We have shown that the index displayed stable outperformance over the cap-weighted benchmark during the live period, as well as stable volatility reduction. These live results are consistent with the long-term back history of the index over 45 years. The average annual excess return across regions in the live period of 3.98% compares to the 3.35% documented in the long US history. Similarly, the observed relative volatility reduction in the live period across regions of 10.30% compares to 10.49% in the long-term track records.

The multi-factor allocation and weighting scheme diversification that the Scientific Beta Multi-Beta Multi-Strategy Four-Factor EW index is built upon helps to avoid the risks associated with pursuing a single strategy and leads to smoother outperformance across time relative to an approach that bets on an individual strategy.

Importantly, the Multi-Strategy-Multi-Beta approach also avoids timing bets. The financial industry is clinging to its old ways and is currently discovering smart beta strategies as grounds for tempting investors to make tactical bets. This involves either enticing investors to chase the performance of the winning smart beta strategies or advocating contrarian bets in the form of valuation-based factor timing. This is an unfortunate development if one considers that smart beta was meant to achieve progress relative to an old world where fund managers and "strategists" claimed that they could make the right call on which part of the market would head up or down in the short term, without any actual evidence that they possess the necessary skill or deliver any true value to investors. Smart beta at the outset has the potential to provide access to evidence-based long-term investment strategies and it would be a pity if market commentators and "strategists" distract from the value of holding such strategies over the long term by turning smart beta strategies into yet another arena for their forecasting contests.

In contrast to such recent developments, the Multi-Beta Multi-Strategy indices do not try to predict the winning strategy or factor. They represent an agnostic view on the capacity to select the winning strategy. In fact, this approach recognises that there is value in combining different strategies that work on average over the long term. Using an index that combines twenty individual strategies (five different weighting schemes applied to four different factor tilts) means that investors will get the average outperformance across the twenty underlying strategies. In the absence of perfect foresight on the future winning strategy, such a broad exposure to a wide variety of strategies is a natural starting point for smart beta investing. Broad exposure to a wide set of strategies may allow investors to sustain their exposure in the long term and help them to consider more serious questions about their investments than asking which smart beta strategy will be the next winner.