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P&I | CONTENT SOLUTIONS GROUP

Research for Institutional Money Management

EDHEC BUSINESS SCHOOL

Defensive when needed?

The Scientific Beta High Factor Intensity (HFI) Low Volatility Maximum Volatility Protection index provides a highly defensive offering with a reduction in the index's market beta in difficult times and very strong protection of the capital.

This offering aims to respond to an important shortcoming in traditional Low Volatility/Minimum Volatility offerings, whose volatility and market exposure increases strongly in periods of very high volatility and therefore crisis periods.

1-Year Rolling Volatility

The analysis runs from 15-Jun-2007 to 30-Jun-2019. The rolling volatility is based on 1-Year daily total returns with a 1-week step size and is annualised. The index used is the SciBeta Developed High-Factor-Intensity Low Volatility Diversified Multi-Strategy Maximum Volatility Protection. We use three different competitor defensive strategies to get an average 1-Year rolling volatility: MSCI World Minimum Volatility, FTSE Developed Minimum Variance and Robeco QI Institutional Global Developed Conservative Equities. Scientific Beta and Bloomberg.

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Risk Awards 2019 Winner | Scientific Beta Indexing firm of the year

PROFESSIONAL PENSIONS INVESTMENT AWARDS 2019
WINNER
Equity Factor Index Provider of the Year
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INTRODUCTION

Introduction to Research for Institutional Money Management supplement in P&I, December 2019

Noël Amenc
Associate Dean for Business Development, EDHEC Business School, CEO, Scientific Beta

It is a pleasure to introduce the latest "Scientific Beta" special issue of the Research for Institutional Money Management supplement to *P&I*.

Set up by EDHEC, a top European academic institution, Scientific Beta wanted this supplement to bring scientific clarity to many questions that are too often approached in an anecdotal way and, in any event, without real and serious empirical evidence. As such, we first investigate whether the performance of factor indexes suffers from stock prices' reactions to rebalancing trades and find that, unlike for cap-weighted indexes, there has been no significant price effect. We argue that index providers should offer information to investors on the price effects generated by their indexes.

We examine whether the Size factor still has its place in multi-factor portfolios. The academic literature sees the Size factor as an important driver of return differences across equity portfolios. In fact, removing the Size factor deteriorates explanatory power more than removing any of the other standard factors does.

Scientific Beta offers investors single smart-factor indexes as long-only or long/short indexes. The indexes, which we describe here, are constructed consistently and seek robustness at all stages of the construction process.

We look at designing more defensive solutions for investors. When constructing a defensive portfolio, the factor-investing approach is more robust than popular optimization techniques. It delivers a similar level of protection in distressed times but also typically exhibits better Sharpe ratios and conditionality.

As alluded to above, despite their positive long-term premium, equity factors experience periods of substantial underperformance. Macroeconomic conditions influence this factor cyclicality. We propose a methodology for analyzing the macroeconomic risk of equity factors, and show that ignoring such risks may lead to under-diversification of multi-factor portfolios.

Smart factor indexes offer exposure to risk factors that are well-rewarded over the long term. There is strong empirical evidence and economic rationale for this. In addition to capturing exposure to factors, the indexes ensure a good reward for these exposures through diversification of unrewarded (specific) risk. Diversification improves long-term risk-adjusted performance while reducing short- and medium-term risk.

We present Scientific Beta's new low-carbon fiduciary option, which is applicable across its entire flagship offering of multi-factor indexes. It addresses the three most common decarbonization objectives for investors: contributing to the transition to a low-carbon economy, reducing the "carbon footprint" of investments, and reducing exposure to climate change risks.

Scientific Beta is also introducing an ESG fiduciary option that is also applicable across its entire flagship offering. This option is relevant to investors who wish to dissociate from controversial companies, demonstrate support of global norms, mitigate reputational and liability risks, or avoid ESG risks with potential adverse financial materiality. These benefits are delivered while retaining the financial outperformance of the standard flagship indexes.

We hope you will find the articles on smart beta in the supplement informative and useful. We extend our warmest thanks to P&I for their partnership on the supplement.

CONTENT

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Are There Price Effects around the Rebalancing of Factor Indexes?

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- **Factor indexes rebalance their positions systematically and transparently at fixed rebalancing dates. We investigate whether the performance of such indexes suffers from the response of stock prices to rebalancing trades and find no significant price effect.**
- **These findings are in stark contrast to results for cap-weighted indexes, for which price reactions around reconstitution events have been substantial.**
- **Our results do not necessarily extend to other factor indexes with different construction rules.**
- **We argue that index providers should offer information to investors on the price effects generated by their indexes.**

SHEDDING LIGHT ON IMPLICIT COSTS

Factor indexes allow investors to pursue systematic investment strategies with low levels of explicit costs. However, some argue that factor indexes may also lead to hidden costs for investors. Index trackers who trade at rebalancing could drive stock prices away from equilibrium levels. Investors may consequently buy stocks at inflated prices and sell them at deflated prices. In addition, the transparency of the rebalancing process may also increase the cost to investors, as other market participants could front-run the index.

For investors it is crucial to know whether these mechanisms create a performance drag, and to understand how such effects can be mitigated. Our study measures price effects for Scientific Beta indexes that have attracted substantial amounts of assets since 2013.

Why Should we Expect Price Effects for Factor Indexes?

Before discussing the empirical evidence, it is useful to ask under which conditions price effects should arise.

Price effects are driven by a lack of substitutes for stocks affected by index changes

Theory does not make a uniform prediction on price effects due to variations in index composition. Rebalancing activity in an index could be absorbed by the market without any price effect or it could generate buying and selling pressure that influences prices. Whether or not there will be price effects depends on how markets work and on the rules of the analyzed index, which may have been designed to mitigate price effects.

A crucial question for price effects is that of substitutability. In extreme cases, investors' demand for a stock that is added to an index may be totally inelastic. They will buy the stock at any price to be able to track the index perfectly. Therefore, stocks added to an index could see important price effects. Such effects could be permanent or, if arbitrageurs help return prices to equilibrium, merely temporary. Standard finance assumes that investors only care about the systematic risk exposures of a given stock. Investors can use substitute stocks that offer the same bundle of systematic risk exposures as a stock that is newly included in an index. This behavior would avoid any price effects.

Price effects could thus arise if factor indexes make it hard for investors to find substitutes. For example, indexes that are highly concentrated in few stocks would pose a replication challenge when investors deviate from the exact index holdings. On the other hand, if a factor index is broadly diversified across a large number of stocks, substituting exact index holdings with portfolio holdings that have similar risk exposures should be easier for index trackers.

Price effects are driven by real benefits of index inclusion

Membership in an index may procure a certification effect and increase investor awareness. Companies in the index could benefit from a benchmark inclusion subsidy in the form of better access to capital markets and lower cost of capital. Such advantages imply that index inclusion raises the value of a company's stock and thus creates a visible price effect. Such effects are plausible for major cap-weighted indexes but less plausible for factor indexes that do not procure "blue-chip" status for their constituent stocks.

Transparency may help to reduce price effects

A common claim is that transparency of rebalancing trades is detrimental to index trackers, as others will trade ahead of them. However appealing, there is no solid theoretical explanation for this argument. Trades by factor index investors do not contain any private[1] information or proprietary insights. Such investors have an incentive to announce their trades. Announcing the trades will signal to liquidity providers that there is no private information involved in the trade. This reduces the risk for liquidity providers, leading them to offer prices that are more competitive. In addition, announcing trades will give liquidity providers the necessary time to prepare for increased demand, thus increasing competition and lowering costs for index trackers. Pre-announcement of index trades, rather than hurting investors, can help to increase competition among liquidity providers and keep costs low.

Are there Price and Volume Effects when Scientific Beta Indexes Rebalance?

We conduct an event study of stocks in Scientific Beta indexes. We look for abnormal returns and volume effects, and compute performance drag. Our methodology accounts for the specifics of factor indexes. First, we avoid selection bias by considering all weight changes in the index rather than focusing only on additions and deletions. Second, we account for event clustering to avoid inflated significance levels. Third, we account for multiple factor exposures when computing abnormal returns. We also run a battery of robustness checks by carrying measures of demand pressure, abnormal returns, and abnormal volume. Our results fail to show any significant price effects around index rebalancing. Cumulative abnormal returns are small and either statistically insignificant or in the opposite direction to the claims about adverse price pressure effects for investors. Estimates of performance drag show that there are no losses for index trackers.

Effects on prices and index performance

To put our results into perspective, we compare them to estimates of abnormal returns around the reconstitution of popular cap-weighted indexes. Exhibit 1 shows the estimated abnormal returns and the confidence interval around the estimates from different studies, each conducted over different time periods. It is clear that the estimate of abnormal returns we find for factor indexes is much smaller than the effects reported for popular cap-weighted indexes.

Exhibit 2 shows the annual performance drag due to index rebalancing effects[2] . The fact that the performance drag is close to zero and even negative suggests that price effects do not hurt the performance of the two Scientific Beta indexes during their rebalancing events.

There are two explanations for why the abnormal returns we estimate for multi-factor indexes are lower than those reported for cap-weighted indexes. First, additions (or deletions) to cap-weighted indexes confer (or remove) a blue-chip status which may affect stocks' long-term value. Second, during the reconstitution events of cap-weighted indexes, trading is concentrated in a few stocks. Since these effects do not arise for the multi-factor indexes we tested, it is not surprising that price effects are negligible.

Effects on trading volume

In addition to price effects, it is interesting to assess how index rebalancing affects trading volume. Even if the market is able to absorb rebalancing trades without any price effect, we may be able to detect volume effects as a more direct consequence of index-rebalancing activity.

We estimate abnormal volumes, defined as the percentage increase in daily volume during the event period. Exhibit 3 shows that the abnormal volume we find (5%) is both insignificant and much smaller than the abnormal volume reported in a study of the S&P 500 (89%). This is in line with the idea that broad diversification and trading constraints will limit demand pressure, even for substantial amounts of assets tracking factor indexes.

[1] *Private information does not signify insider information; it could be the result of superior insights due to proprietary analysis of public information.*
[2] *Note that the performance drag from any price effects would also be included in index performance, as long as it consists of a live track record during times when actual investments replicating the index took place.*

CONCLUSION: TOWARDS GREATER TRANSPARENCY

Our analysis of Scientific Beta multi-factor indexes shows no price effects around index rebalancing that would worsen performance for index investors. Importantly, our results apply to the particular indexes and the sample studied in our paper. They do not allow general conclusions to be drawn about whether any other factor index generates price effects. In particular, the indexes we study limit demand pressure on stocks through investibility constraints and broad diversification. Indexes that omit these features could fare differently when tested for price effects.

Some claim that smart beta indexes are too transparent, because intuition suggests that transparency could create price effects at rebalancing. We argue instead that there is too little transparency. Most index providers do not provide investors with an assessment of price effects around the rebalancing of their indexes. Whether there are price and volume effects for a given index can be determined by analyzing the data. Index providers should offer more analytics and more transparency to allow for factual analysis. •

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EXHIBIT 1

Comparison of price effects across different studies

Comparison of cumulative abnormal return at effective date (ED) across different studies. For Scientific Beta we report the results obtained with Weight Change as the sorting measure. Confidence Interval is the estimate +/- 1.96 Std. Errors. Based on results reported in the original studies. For Scientific Beta indexes the sample period starts at the inception date of the indexes (December 2013) and ends on March 2018.

Cumulative Abnormal Returns and Confidence Interval

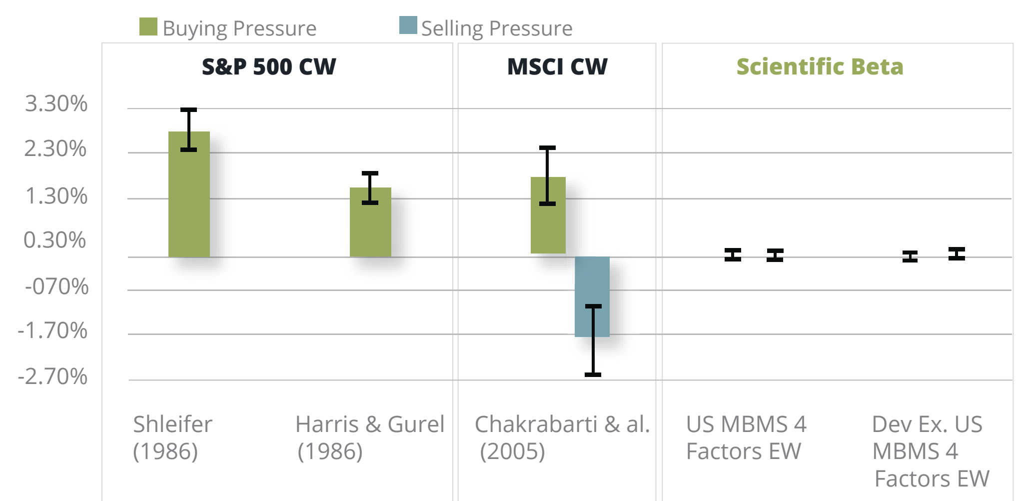


EXHIBIT 2

Performance drag

The table reports the annualized average performance drag (PD) from December 2013 to March 2018 (live period) of the US Multi-beta multi- strategy 4 factors EW and the Dev. ex- US Multi-beta multi-strategy 4 factors EW. We report the PD obtained using the CAR estimated with the characteristics based methodology of Daniel et al. (1997) for two event windows, AD:ED and ED. The demand pressure used for selecting the stocks is Weight Changes.

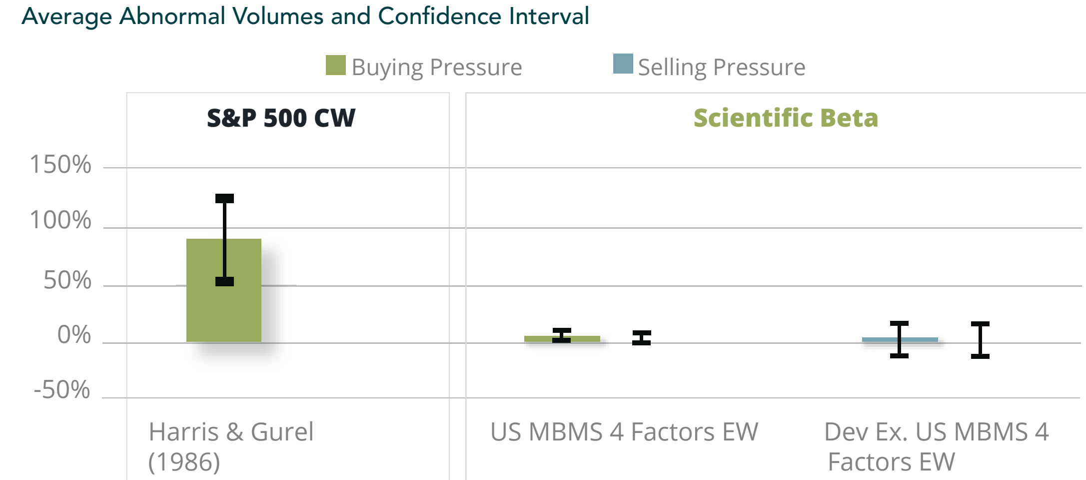
Event Date	US MBMS 4-Factors EW December 2013-March 2018	Dev. Ex-US MBMS 4-Factors EW December 2013-March 2018
AD:ED	-0.02%	-0.07%
ED	0.00%	-0.01%

EXHIBIT 3

Comparison of volume effects across different studies

Comparison of average abnormal volume at effective date (ED) across different studies. For Scientific Beta we report the results obtained with Weight Change as the sorting measure. Confidence Interval is the estimate +/- 1.96 Std. Errors. Based on results reported in the original studies.

Average Abnormal Volumes and Confidence Interval



Is There Still a Role for the Size Factor in Multi-Factor Portfolios?

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- **It is well established that stocks with smaller market capitalization outperform large stocks over the long term, yet asset managers often remove Size from the factor menu given its relatively weak post-publication performance.**
- **Instead of looking at the stand-alone performance, we use cross-factor correlation to assess the impact of excluding the Size factor.**
- **Our results suggest that the Size factor improves model fit, delivers a significant positive premium in the presence of other factors, and contributes positively to the performance of multi-factor portfolios.**
- **Omitting the Size factor has substantial cost to investors that often exceeds that of omitting other popular factors.**

The Size factor is well established in financial literature – stocks with small market capitalization outperform larger stocks over the long-term – but this concept has recently come under attack from smart beta providers. The reason is simple. Its performance has lagged behind that of other factors. A common response is to recommend removing Size from the factor menu, to give more weight to factors with better performance.

We take issue with this recommendation, which is in stark contradiction with the academic evidence on factor models of equity returns. The academic literature sees the Size factor as an important driver of return differences across equity portfolios. In fact, removing the Size factor deteriorates explanatory power more than removing any of the other standard factors does.

Where does this difference in judgement on the Size factor come from? Smart beta providers typically compare the performance of Size to other factors. When testing asset-pricing models, academics ask whether a factor carries information not captured by the other factors in the model. In other words, they account for interaction across factors. Similarly, investors are interested in how a factor contributes to investment outcomes when used alongside other factors. Even if it does not have the highest returns, a factor is useful if it provides diversification benefits with respect to other factors.

THE SIZE PREMIUM

Exhibit 1 shows factor premia in US equities over the past 55 years. The Size factor only had a 0.24% monthly return. While this is significantly different from zero, it falls short of the returns achieved by other standard factors. The Momentum and Low Risk factors had premia that were roughly three times larger.

However, for multi-factor investors the relevant question is whether the Size factor delivers a premium after adjusting for implicit exposures to the other factors. Among the implicit exposures, we account for the Market, Value, Momentum, Low Risk, High Profitability and Low Investment factors. Similar to the adjusted Size premium, we obtain adjusted premia for each of the standard factors.

The Size factor still generates a significant premium after adjustment. In fact, its premium remains unchanged compared to its stand-alone return. For the other factor premia, we observe a reduction when we account for their implicit exposures. The reduction is strongest for the Value, Low Risk and Low Investment factors. This suggests that returns of these factors are partly explained by their implicit exposures. After adjustment, the Size premium is at least as high as the Value, High Profitability and Low Investment premia. Only Momentum and Low Risk still show a higher premium than Size.

We stress the finding that the implicit exposures of the Size factor have no impact on its premium. It delivers returns that are unrelated to other factors, making it a valuable component in multi-factor portfolios.

THE ROLE OF SIZE IN MULTI-FACTOR PORTFOLIOS

We have assessed factor allocations that maximize the risk/return ratio over our long-term period of analysis. We find that Size receives a weight of more than 9% in the optimal portfolio, which is greater than that of Value (3%), and close to that of Momentum (11%) and Low Risk (12%). This result is striking. Recall that the average returns of Momentum and Low Risk were about three times higher than the returns of Size. Yet, the optimal allocation to Size is only slightly lower than the allocation to Momentum and Low Risk.

Despite a lack of stellar returns, the Size factor improves the risk/return properties of a multi-factor portfolio. Of course, an optimal portfolio will allocate to a factor not only based on returns, but also based on volatility and correlation with the other factors.

To assess the relevance of each factor for a diversified multi-factor portfolio, we can ask the following question: what is the hypothetical level of return at which the factor becomes unattractive to an investor? We can answer this question by gradually decreasing the return assumption for a given factor until the optimal portfolio assigns zero weight to it. If the premium of a factor were at this indifference level, investors would not get any benefits from including it in their portfolio.

Exhibit 2 shows the indifference level compared to the historical average return. Even at a return of zero, the Size factor deserves inclusion in a multi-factor portfolio. In contrast, the Low Risk factor would cease to add any value to a portfolio even with returns as high as 0.52% per month. The Value factor is no longer attractive if we reduce its expected return to 0.28% per month, which is only four basis points below its historical average. Somewhat similar to the Size factor, the Momentum and High Profitability factors would tolerate substantial reductions in premium before warranting exclusion.

Why do some factors remain attractive after a sizable reduction in their premium? It is because they provide diversification benefits in addition to contributing to returns. A factor that provides strong diversification benefits will receive a positive weight, even if we assume that its premium is low. A low indifference premium thus reflects strong diversification benefits.

Size is one of the factors with the most pronounced diversification benefits. Therefore, it would be included in the optimal portfolio, even if its average return were close to zero. The fact that Value and Low Risk need to command a relatively high premium reflects that they have low diversification benefits relative to the other factors in the menu.

We find similar diversification benefits of the Size factor when accounting for macroeconomic conditions. For example, Size is less sensitive to interest rate shocks than other factors. Exposure to the Size factor allows investors to counterbalance the high interest rate sensitivity of factors like Value, Low Risk and Low Investment. •

CONCLUSION: THE SIZE FACTOR IS ALIVE AND WELL

Our analysis differs from recent studies by smart beta providers in how we assess the relevance of the Size factor. Rather than asking which factor has the highest stand-alone performance, we ask what the marginal impact of the Size factor is when including it in the menu along with other factors.

First, we find that exclusion of the Size factor from a multi-factor asset-pricing model leads to a substantial increase in the proportion of unexplained returns of portfolios sorted by characteristics. This suggests that excluding Size seriously deteriorates model fit. Second, we find that the Size premium is economically and statistically significant over the long-term US history when accounting for the presence of other commonly used equity factors. The average return of the Size factor that is unrelated to implicit exposure to other factors is not only significantly positive, it is also similar in magnitude to the premia from other factors, and at least as high as those of Value, Low Investment, and High Profitability. Third, the analysis of mean-variance efficient portfolios suggests a sizable role for the Size factor. Its diversification effects mean that the Size factor would keep a role in the optimal multi-factor portfolio even if the Size premium were substantially lower than what was observed historically. Similarly, Size exposure allows investors to diversify macroeconomic risks,

EXHIBIT 1

Equity Factor Premia (monthly average)

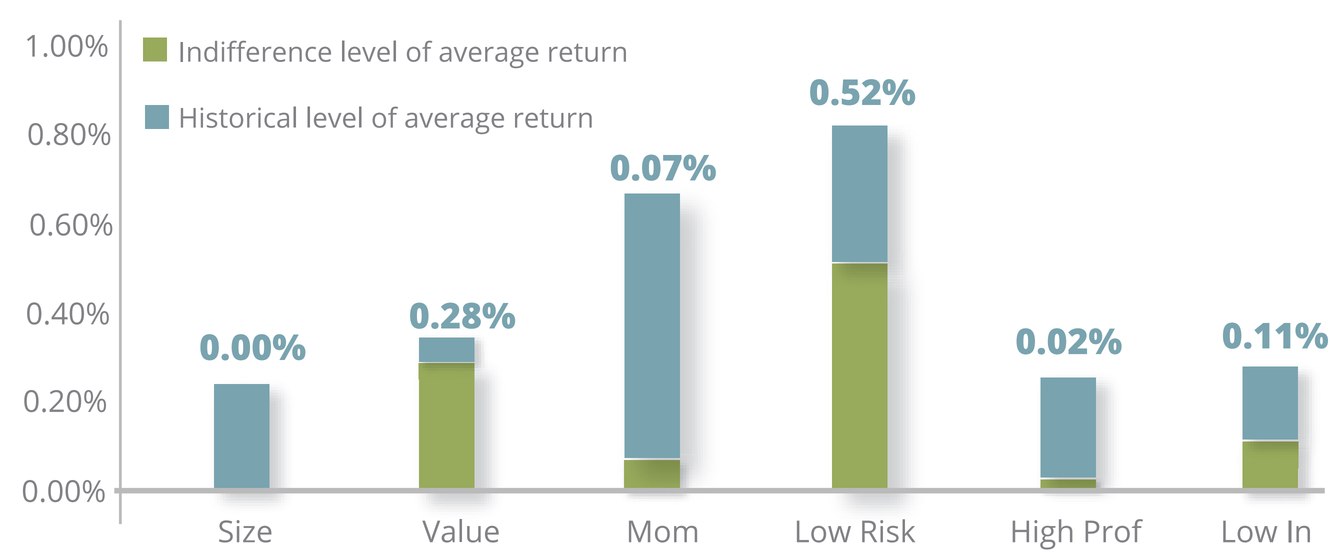
The table reports average monthly returns and average monthly alpha from a six-factor model that includes all the factors other than the dependent variable. Data is for US equities from July 1963 to December 2018. T-statistics are reported in the parenthesis. Coefficients, which are significant at the 5% level are highlighted in bold.

	Size	Value	Mom	Low Risk	Hi Prof	Low Inv
Average Return						
	0.24%	**0.32%**	**0.66%**	**0.83%**	**0.26%**	**0.28%**
	(2.04)	(2.99)	(4.10)	(6.53)	(3.06)	(3.64)
Returns adjusted for exposure to other factors						
	0.24%	0.04%	**0.59%**	**0.30%**	**0.24%**	**0.16%**
	(2.09)	(0.45)	(3.68)	(2.65)	(3.14)	(3.04)

EXHIBIT 2

Indifference level of return vs historical level (monthly average)

Reported figures correspond to expected returns at which the weight for the given factor in the mean-variance efficient (MVE) portfolio becomes zero. Data for US Equities from July 1963 to December 2018



such as interest rate risk.

Importantly, the cost of omitting the Size factor is as high as the cost of omitting other factors. Except when considering the stand-alone factor premium, Size never shows up as the worst- performing factor among the factors included in the analysis. So it is true that if your objective had been to pick the best performing factor, Size would not have been a good choice historically, but if you were looking to hold a diversified factor portfolio, it would have been a valuable addition. Due to its low correlation with other factors, Size offers substantial diversification benefits. Investors need to look beyond stand-alone performance and consider such diversification benefits when selecting factors.

For full references and complete methodology, please see the unabridged paper at: Does the Size Factor Still Have Its Place in Multi-Factor Portfolios? Scientific Beta White Paper, July 2019. •

How to Achieve Good Reward and Sound Risk Management with Single Factor Indexes

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- **Scientific Beta's indexes help investors to achieve exposure to rewarded risk factors; they offer high exposure to the desired factor tilt as well as strong overall factor intensity**
- **Investors also benefit from additional controls in the stock selection mechanism that support diversification of unrewarded elements**
- **Scientific Beta's consistent four-step construction process is designed with a focus on robustness**
- **Significantly, it enables investors to reconcile strong factor exposure to desired risk factor and high factor intensity**

The key principles of Scientific Beta's investment philosophy are based on the Smart Beta 2.0 methodology (see Exhibit 1) introduced by Amenc and Goltz (2013):

- Offering exposure to long-term rewarded risk factors;
- Ensuring a good reward for these factors through good diversification of unrewarded (specific) risk; and
- Guaranteeing sound risk management of the investment by implementing risk allocation between well-diversified factor indexes and the capacity to control implicit risks of factor investing such as sector, country or market beta gap risks.

The application of Scientific Beta's investment principles as described in Exhibit 1 provides investors with a robust menu of single long only and long/short factor indexes that rely on academically validated long-term rewarded risk factors. They offer high exposure to their desired factor tilt as well as strong overall factor intensity, thanks to the application of a High-Factor- Intensity filter that removes stocks with strong negative factor interactions. Moreover, they support diversification of unrewarded risks with our well designed Diversified Multi-Strategy weighting scheme. The long-term risk premium associated with the desired factor tilt can be captured efficiently while reducing idiosyncratic risk. For all these reasons, Scientific Beta single smart factor indexes offer better long-term risk-adjusted performance and attractive conditional performance.

A Four-Step Construction Design with Focus on Robustness

Scientific Beta attaches great importance to the robustness of its indexes. The robustness is based on six good practices:

1. The search for broad academic consensus on the choice of factors and their definition.
2. The concern for parsimony, whether it involves the choice of factor proxy or the parameters to be estimated to implement the diversification of the portfolios representing the factors.
3. The requirement for strong consistency in the index construction methods.
4. The search for the best possible performance, not through optimization techniques based on stock returns or characteristics, but through good diversification of unrewarded risks.
5. The capacity to respect the governance of investment risks by ensuring that the factor exposure choices selected by the investor do not result in unwanted exposure to hidden risks, like geography, sector or market beta gap risks. These implicit exposures are not rewarded and distort the sources of performance of the strategy.
6. The implementation of thorough robustness tests that are notably based on an analysis of conditional performance in a multi-dimensional context (market, volatility, sector, factors) and also on an evaluation of robust statistical inference and on out-of-sample robustness tests of the performance and risk of the indexes proposed using long-term data.

Scientific Beta's construction process for single smart factor indexes relies on four main steps, which are summarized in Exhibit 2.

The first step is to tilt towards academically validated factors. Extensive empirical research over the past decades discovered hundreds of "rewarded" factors, also known as the "factor zoo". However, only a few have survived academic scrutiny. This set of factors that appears consistently in consensus models of expected return is not only relatively small, but also very stable over time. Respecting parsimonious factor definitions validated by independent academic research protects investors against the robustness risks of proprietary back-tested, and possibly data-mined, factor innovations. We retained six factors for which there is a broad academic consensus, namely Size, Value, Momentum, Low Volatility, High Profitability and Low Investment, which are constructed based on one proxy definition. The proxy used is the one used in the academic literature to justify the existence of the risk premium. This selection ensures robustness of our proxy, since we avoid data-mining and sample dependency of proprietary factor definitions and use of multi-proxies.

The second construction step consists in addressing negative interaction effects between factors. Focusing only on stocks with the highest or lowest factor scores ignores the potential interaction effects with other risk factors. For instance, a stock with a low volatility score might also have a low value score. A single smart factor index might therefore have a positive exposure to a desired factor tilt but low or even negative exposures to other rewarded risk factors. Thus, investors would benefit from additional controls in the stock selection mechanism to account for such interaction effects. Scientific Beta uses a High-Factor-Intensity (HFI) filter, which eliminates those stocks with the worst multi-factor scores[3]. The HFI filter is used for long only indexes or for the long branch of long/short indexes. For short branches of long/short indexes, we also need to take into account factor interaction, but the objective of the short branch is to have the worst exposure to the desired factor tilt, therefore, in this case, we use an anti-HFI filter, which eliminates stocks with the best multi-factor scores. Taking into account negative interaction effects between factors allows single factor indexes to achieve strong factor intensity over the long-term.

In Exhibits 3a and 3b, we recap our stock selection process. We have two types of selection, i.e. standard HFI and narrow HFI. For the standard HFI selection, which is used in our flagship Multi- Beta Multi-Strategy smart factor indexes, we select 50% of stocks based on the factor score and exclude those, within the factor-based selection, with the lowest multi-factor score, leaving 30% of stocks compared to the starting investment universe. To obtain more exposure to the desired factor tilt, we also have an alternative process, the narrow HFI selection. The stock selection process starts with a narrower number of stocks that contains only 30% of the entire universe, and filters out a smaller number, leaving 20% of stocks compared to the starting investment universe at the end of the process. The narrow HFI filter corresponds to investors favoring the highest factor exposure to a desired factor tilt. We highlight that our single long only indexes can be based on both stock selection process, while our long/short indexes are based on the standard HFI process, i.e. with a 30% final stock selection.

The third step consists of diversifying exposure to idiosyncratic risks. Indeed, factor portfolios should diversify specific risk to improve long-term risk-adjusted performance

[3] For long only indexes of long branches of long/short indexes, the multi-factor score is composed of the value, momentum, volatility, investment and profitability scores. Stocks with the lowest multi-factor scores are removed. Alternatively, for short branches of long/short indexes, the multi-factor score is composed of the size, value, momentum, volatility, investment and profitability scores. Stocks with the highest multi-factor scores are removed. Using an anti-HFI filter in the short branch of long/short indexes allows factor interaction to be taken into account and therefore improves the factor intensity of long/short indexes.

and performance robustness. We achieve diversification by using four popular weighting schemes, i.e. Maximum Deconcentration, Diversified Risk Weighted, Maximum Decorrelation and Efficient Maximum Sharpe Ratio. This Multi-Strategy approach reduces model and estimations risks in portfolio construction[4].

The last step is the control of hidden risks, which is present in numerous implementations of factor investing solutions. In an investment world where different risk dimensions are rarely orthogonal, the design of smart beta solutions has a direct impact on exposures to other implicit risks. Scientific Beta attaches great importance to recognizing them and, if needed, to reducing them through risk control options. For a multi-regional universe, we aggregate each Geographic Basic Block by its free-float market capitalization in the reference cap-weighted index. This approach prevents regional bets being taken. Sector risk is generally accompanied by fairly high tracking error with respect to the cap-weighted index and greater exposure to macroeconomic factors. Scientific Beta offers a Sector Neutral risk control option for all of its single long only smart factor indexes, while it is integrally part of the construction of single long/short indexes[5]. This option mitigates the consequences of severe under or over exposure to some sectors due to factor tilting. We note that for long/short indexes, sector neutrality is not defined with respect to the broad cap- weighted index but relative to sector representativeness. Indeed, cap-weighted indexes are concentrated and do not provide sector diversity in terms of number of stocks included in the universe. Using this method allows sector diversity to be improved as well as stock deconcentration.

Finally, for our long/short indexes only, in addition to sector neutrality, we impose market beta neutrality[6]. Market beta neutrality is paramount in a long/short context, since the premium from long/short risk factors is, on average, lower than the market premium. Therefore, ensuring market beta neutrality allows to hedge out market risk and to benefit solely from the risk factor premium. In measuring the market betas of multi-factor indexes or strategies, we identify three challenges that need to be addressed. First, unlike cap-weighted indexes, multi-factor strategies or indexes change stock composition frequently. Therefore estimating market betas using the historical portfolio returns does not give an accurate description of the current market beta of the index. Second, the strong variability in stock level betas always makes the ex-ante estimation in a determined sample specific. Last, the choice of the factor model used in the beta estimate also plays an important role in determining the robustness of beta. Extensive research has shown that the use of several models reduces model risk, especially when the models used rely on fairly different assumptions with strong justification for the use of each. Scientific Beta has developed an estimation method for market beta that takes into account these three challenges:

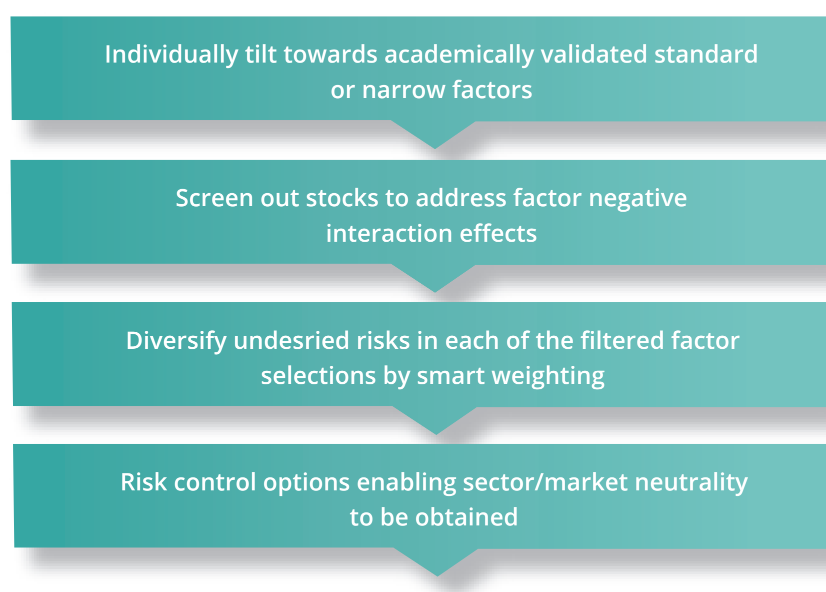
i. We take the current stock composition of the index into account and therefore derive index market beta as an average of stock market betas, weighted at the current portfolio weights;
ii. We use Bayesian shrinkage techniques to reduce the estimation sample dependency;
iii. We implement model averaging using three different estimation methods (Ordinary Least Squares, Weighted Least Squares and Kalman Filter).

EXHIBIT 1

Key Principles of Scientific Beta's Investment Philosophy

EXHIBIT 2

Scientific Beta Construction Steps



Reconcile Strong Factor Exposure to Desired Risk Factor and High Factor Intensity

Our single smart factor indexes offer exposure to academically validated risk factors while ensuring a high risk-adjusted performance over the long-term through the diversification of unrewarded risks. Indeed, it is clear from Exhibit 3c that single long only indexes provide an average improvement to the Sharpe ratio of 67% relative to the cap-weighted index. Similarly, single long/short indexes provide an average improvement of 106%. We underline that single long/short indexes have very low volatility compared to the cap-weighted index, in the range of 2.6-3.7%. This is explained by the risk management focus used in the construction process, such as sector and market beta neutrality. In addition, we emphasize that the out-of-sample market beta of long/short indexes is close to 0, which provides very good market conditionality for the performances, as can be seen in Exhibit 3c.

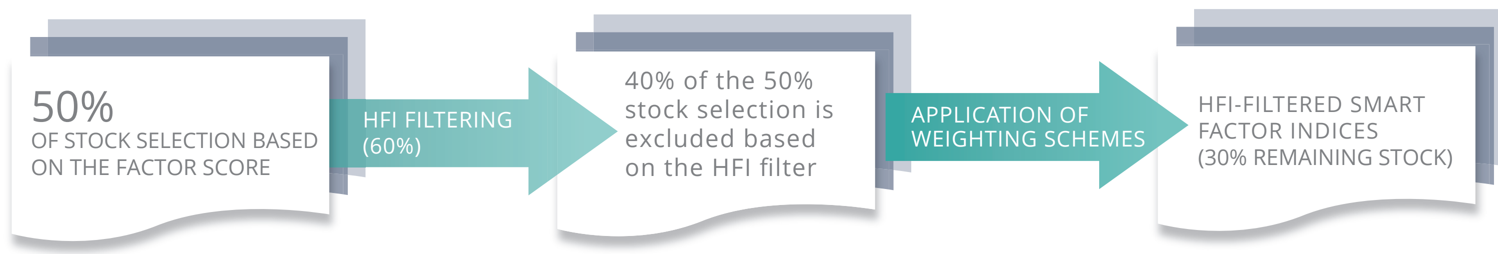
Exhibit 4 shows the exposure of our single smart factor indexes to their desired factor tilt and their factor intensity. We underline the strong factor intensity of all our indexes, whether standard HFI or narrow HFI long only indexes as well as our long/short indexes. This is the direct benefit of using the HFI filter in the construction step to remove stocks with negative factor interactions.

Finally, our long/short indexes exhibit very low conditionality to market bull/bear regimes, since they

[4] *See Amenc et al. (2014).*
[5] *Note that for long/short indexes, sector neutrality is not defined with respect to the reference Cap-Weighted index, but instead based on the sector representativeness in terms of number of stocks in the universe.*
[6] *Branches are rebalanced every month to ensure market beta neutrality.*

EXHIBIT 3

3a. Stock selection with High Factor Intensity (HFI) filter



3b. Stock selection with narrow High Factor Intensity (HFI) filter

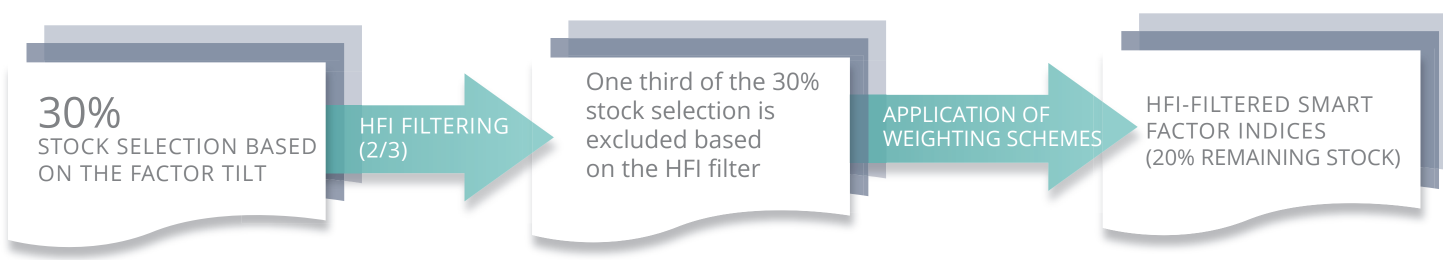


EXHIBIT 3c

Performance of single long only and long/short indexes on SciBeta Developed universe

We use daily total return data in USD from June 18, 2004 to June 30, 2019. The cap-weighted index is the SciBeta Developed Cap- Weighted index. Long only indexes used are the SciBeta Developed HFI Mid-Cap DMS (4-Strategy), SciBeta Developed HFI Value DMS (4-Strategy), SciBeta Developed HFI High Momentum DMS (4-Strategy), SciBeta Developed HFI Low Volatility DMS (4-Strategy), SciBeta Developed HFI High Profitability DMS (4-Strategy) and SciBeta Developed HFI Low Investment DMS (4- Strategy). Long/short indexes used are prototypes of long/short indexes based on the following tilts: Mid-Cap, Value, High Momentum, Low Volatility, High Profitability, Low Investment on the SciBeta Developed universe. EW is an equally-weighted portfolio of the single indexes.

June 18, 2004 to June 30, 2019	CW	Mid-Cap	Value	Momentum	Low Volatility	Profitability	Investment	EW
Single Long Only								
Ann. Returns	7.78%	10.43%	10.92%	10.56%	10.83%	10.95%	10.54%	10.72%
Ann. Volatility	15.28%	13.63%	14.08%	14.00%	12.12%	13.13%	13.15%	13.25%
Sharpe Ratio	0.42	0.67	0.68	0.66	0.79	0.73	0.70	0.71
Sharpe Ratio Improvement	-	58%	61%	56%	86%	74%	66%	68%
Max Drawdown	57.1%	53.7%	51.9%	50.6%	46.2%	47.7%	48.2%	49.7%
Market Beta	1.00	0.87	0.91	0.91	0.78	0.85	0.85	0.86
Single Long Only								
Ann. Returns	7.78%	2.88%	1.20%	2.49%	3.55%	3.31%	2.32%	2.65%
Ann. Volatility	15.28%	2.92%	2.78%	3.73%	3.29%	2.83%	2.60%	1.97%
Sharpe Ratio	0.42	0.99	0.43	0.67	1.08	1.17	0.89	1.34
Sharpe Ratio Improvement	-	133%	2%	58%	155%	176%	111%	218%
Max Drawdown	57.1%	13.5%	12.5%	17.3%	10.1%	6.0%	7.3%	7.5%
Market Beta	1.00	0.01	0.00	0.01	0.03	0.01	0.00	0.01

EXHIBIT 4

Factor exposure of single long only and long/short indexes on SciBeta Developed universe

We use daily total return data in USD from June 18, 2004 to June 30, 2019. The cap-weighted index is the SciBeta Developed Cap- Weighted index. Long only – Standard HFI indexes used are the SciBeta Developed HFI Mid-Cap DMS (4-Strategy), SciBeta Developed HFI Value DMS (4-Strategy), SciBeta Developed HFI High Momentum DMS (4-Strategy), SciBeta Developed HFI Low Volatility DMS (4-Strategy), SciBeta Developed HFI High Profitability DMS (4-Strategy) and SciBeta Developed HFI Low Investment DMS (4-Strategy). Long only – Narrow HFI indexes used are the SciBeta Developed Narrow HFI Mid-Cap DMS (4- Strategy), SciBeta Developed Narrow HFI Value DMS (4-Strategy), SciBeta Developed Narrow HFI High Momentum DMS (4- Strategy), SciBeta Developed Narrow HFI Low Volatility DMS (4-Strategy), SciBeta Developed Narrow HFI High Profitability DMS (4-Strategy) and SciBeta Developed Narrow HFI Low Investment DMS (4-Strategy).Long/short indexes used are prototypes of long/short indexes based on the following tilts: Mid-Cap, Value, High Momentum, Low Volatility, High Profitability, Low Investment on the SciBeta Developed universe. EW is an equally-weighted portfolio of the single indexes.

June 18, 2004 to June 30, 2019	Mid-Cap	Value	Momentum	Low Volatility	Profitability	Investment	EW
Single Long Only - Standard HFI							
Exposure to desired factor tilt	0.31	0.27	0.32	0.33	0.34	0.25	-
Factor Intensity (Int)	0.80	0.80	0.76	0.74	0.83	0.80	0.79
Single Long Only - Narrow HFI							
Exposure to desired factor tilt	0.34	0.34	0.45	0.45	0.47	0.38	-
Factor Intensity (Int)	0.86	0.81	0.64	0.71	0.94	0.85	0.80
Single Long Short							
Exposure to desired factor tilt	0.31	0.55	0.43	0.35	0.38	0.37	-
Factor Intensity (Int)	0.93	1.23	0.79	0.88	0.81	0.98	0.94

deliver positive returns in both states and their bull/bear spread return is close to zero. This is a direct consequence of the accuracy of our market-beta-forecasting model. Furthermore, we emphasize the good conditionality of our long/short indexes in bull/bear desired-factor-tilt regimes, thanks to the strong overall factor intensity and the good diversification of the idiosyncratic risk of these indexes. Indeed, they deliver strong positive returns when the desired factor tilt is bullish, whereas they deliver slightly negative or lower negative returns in magnitude when the desired factor tilt is in bear regimes.

To conclude, Scientific Beta single smart factor indexes are offered to investors as long only or long/short indexes. They are constructed consistently and seeking robustness at all stage of the construction process and they offer:

i. Good factor exposure to desired factor tilt through exposure to academically validated risk factors;
ii. Good factor deconcentration meaning that they are not only exposed to their desired factor tilt but also to other rewarded risk factors that improve their absolute robustness. Indeed, they will be less impacted in bear periods of the desired factor tilt;
iii. High risk-adjusted performance over the long-term through the diversification of unrewarded risks; and
iv. Risk control options that allows exposures to hidden risks such as geographic, sector or market-beta-gap risks to be reduced. •

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EXHIBIT 5a

Conditional performance of single long only standard HFI indexes on SciBeta Developed

We use daily total return data in USD from June 18, 2004 to June 30, 2019. Bull (Bear) regimes are defined as months where market or the desired factor tilt posted positive (negative) returns. Bull and Bear relative returns are returns in excess of the market in the defined regime. Relative Spread is the difference between bull relative returns and bear relative returns. Bold numbers are statistically significant at the 5% level. Conditional ratio is defined as follows: raw ratio = abs(bull relative return - bear relative return) / (bull relative return + bear relative return) and conditional ratio = k * exp(ratio) / exp(1 + ratio) - k/2 where k = 4. When the raw ratio is negative the conditional ratio is set at 2. Market is the SciBeta Developed Cap-Weighted index. Desired factor tilt L/S regressors that are market beta neutralized ex-post every quarter. Indexes used are the SciBeta Developed HFI Mid-Cap DMS (4-Strategy), SciBeta Developed HFI Value DMS (4-Strategy), SciBeta Developed HFI High Momentum DMS (4-Strategy), SciBeta Developed HFI Low Volatility DMS (4-Strategy), SciBeta Developed HFI High Profitability DMS (4- Strategy) and SciBeta Developed HFI Low Investment DMS (4-Strategy). EW is an equally-weighted portfolio of the single indexes.

June 18, 2004 to June 30, 2019 (RI/USD)	Mid-Cap	Value	Momentum	Low Volatility	Profitability	Investment	EW
Bull/Bear Market regimes							
Bull Rel. Ret	-0.80%	0.58%	0.42%	-5.85%	-2.13%-	2.43%	-1.70%
Bear Rel. Ret	5.19%	4.85%	4.30%	10.70%	7.39%	6.85%	6.53%
Rel. Bull/Bear Spread	**-5.99%**	**-4.27% -**	**3.88%**	**-16.55%**	**-9.52%**	**-9.28%**	**-8.23%**
Conditional Ratio	1.19	0.75	0.78	1.87	1.44	1.56	1.39
Bull/Bear Desired Factor Tilt regimes							
Bull Rel. Ret	5.87%	6.43%	8.17%	8.62%	6.11%	5.42%	-
Bear Rel. Ret	-0.25%	0.12%	-4.69%	-6.98%	-0.99%	-0.21%	-
Rel. Bull/Bear Spread	**6.12%**	**6.30%**	**12.86%**	**15.60%**	**7.11%**	**5.63%**	-
Conditional Ratio	0.99	0.89	1.90	2.00	1.20	0.99	-

EXHIBIT 5b

Conditional performance of single long/short indexes on SciBeta Developed

We use daily total return data in USD from June 18, 2004 to June 30, 2019. Bull (Bear) regimes are defined as months where market or the desired factor tilt posted positive (negative) returns. Bull and Bear relative returns are returns in excess of the market in the defined regime. Relative Spread is the difference between bull relative returns and bear relative returns. Bold numbers are statistically significant at the 5% level. Conditional ratio is defined as follows: raw ratio = abs(bull relative return - bear relative return) / (bull relative return + bear relative return) and conditional ratio = k * exp(ratio) / exp(1 + ratio) - k/2 where k = 4. When the raw ratio is negative the conditional ratio is set at 2. Market is the SciBeta Developed Cap-Weighted index. Desired factor tilt L/S regressors that are market beta neutralized ex-post every quarter. Indexes used are prototypes of long/short indexes based on the following tilts: Mid-Cap, Value, High Momentum, Low Volatility, High Profitability, Low Investment on the SciBeta Developed universe. EW is an equally-weighted portfolio of the single indexes.

June 18, 2004 to June 30, 2019 (RI/USD)	Mid-Cap	Value	Momentum	Low Volatility	Profitability	Investment	EW
Bull/Bear Market regimes							
Bull Rel. Ret	3.45%	1.53%	1.98%	2.90%	2.97%	2.07%	2.50%
Bear Rel. Ret	1.75%	0.55%	3.29%	4.73%	3.97%	2.64%	2.85%
Rel. Bull/Bear Spread	1.70%	0.98%	-1.31%	-1.84%	-1.00%	-0.56%	-0.34%
Conditional Ratio	0.32	0.46	0.25	0.24	0.14	0.12	0.06
Bull/Bear Desired Factor Tilt regimes							
Bull Rel. Ret	5.99%	8.45%	10.01%	10.68%	6.00%	7.60%	-
Bear Rel. Ret	-0.58%	-5.10% -	6.96%	-8.24%	-0.73%	-3.70%	-
Rel. Bull/Bear Spread	**6.57%**	**13.54%**	**16.97%**	**18.92%**	**6.73%**	**11.29%**	-
Conditional Ratio	1.08	1.93	1.98	2.00	1.13	1.79	-

How to Design More Defensive Factor Solutions

Daniel Aguet
Head of Indices
Scientific Beta

Marcel Sibbe
Quantitative Equity Analyst
Scientific Beta

- **When constructing a defensive portfolio, the factor investing approach is more robust than popular optimization techniques.**
- **It delivers a similar level of protection in distressed times but also typically exhibits better Sharpe ratios and conditionality.**
- **Scientific Beta offers a choice of defensive solutions based on low-volatility factor exposure, allowing investors to focus either on collecting the factor's risk premium or protecting their portfolio against deteriorating market conditions.**
- **For the former, the HFI low-volatility or the narrow low-volatility indexes provide good exposure; for the latter, the Scientific Beta indexes that benefit from the maximum-volatility risk-control option are the best fit.**

Defensive strategies offered to investors are based on either optimization techniques or factor investing approach[7]. The first method uses optimization techniques to obtain the portfolio with the lowest possible volatility. We consider that this tactic is not robust, since it is known to produce concentrated portfolios, negative exposures to other rewarded factors, and is sensitive to parameter estimations and outliers. The second approach harvests the Low Volatility risk factor and is the method favored by Scientific Beta[8].

Exhibit 1 compares the performance of our defensive indexes to that of the MSCI Minimum Volatility index, which is representative of optimization-type solutions. We observe that, on average, all solutions provide a volatility reduction of between 18% and 26% and give an exposure to the Low Volatility factor, ranging from 0.22 to 0.43. They deliver similar levels of protection in distressed times, which are defined either by bear or high-volatility market regimes. However, SciBeta Defensive indexes exhibit better Sharpe ratios and conditionality than a popular defensive index such as the MSCI Minimum Volatility index, especially when the Low Volatility factor is underperforming. This is due to the Scientific Beta construction process and especially to:

i. The diversification of unrewarded risks to capture efficiently the Low Volatility premium and deliver high risk-adjusted performance over the long-term;

ii. The use of the High Factor Intensity (HFI) filter. The latter removes stocks with negative factor interactions and improves the exposure to all other rewarded risk factors. When the Low Volatility factor is underperforming, our indexes benefit from their exposures to other well-rewarded risk factors to reduce the underperformance.

Our defensive offering is robust and delivers, on average, good protection to investors in distressed times. Nevertheless, average risk measures are misleading and the volatility of low-volatility is not always low. Indeed, we observe in Exhibit 2 the one-year rolling volatility of our defensive solutions as well as the MSCI Minimum Volatility

EXHIBIT 1

Key statistics metrics of SciBeta Defensive offering and MSCI Minimum Volatility

The analysis is based on daily total returns in USD from June 21, 2002 (base date of SciBeta indexes). to June 30, 2019. All statistics are annualized. Yield on Secondary U.S. Treasury Bills (3M) is used as a proxy for the risk-free rate. Bull (bear) market regimes are defined as months with positive (negative) market returns. Bull (bear) Low Volatility regimes are defined as months with positive (negative) Low Volatility regressor returns. Low (High) volatility market regimes are defined as 50% months with the lowest (highest) volatility. Factor intensity is the sum of all non-market factor exposures. Regressions are performed using weekly returns. The smart factor indexes used are the SciBeta Developed High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy), SciBeta Developed High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy) (Sector Neutral) and the SciBeta Developed Narrow High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy) and the MSCI World Minimum Volatility. The cap-weighted index is the SciBeta Developed Cap-Weighted.

June 20, 2001 to June 30, 2019 (RI/USD)	CW Index	Standard HFI	Sector Nuetral HFI	Narrow HFI	MSCI Min Vol
Ann. Returns	8.19%	11.31%	10.90%	10.90%	9.10%
Ann. Volatility	15.39%	12.00%	12.66%	11.35%	11.43%
Volatility Reduction	-	**-22%**	**-18%**	**-26%**	**-26%**
Sharpe Ratio	0.45	0.83	0.76	0.85	0.68
Sharpe Ratio Improvement	-	**86%**	**69%**	**89%**	**52%**
Market Beta	1.00	0.77	0.82	0.72	0.70
Exposure to Low Volatility	0.00	0.32	0.22	0.43	0.41
Factor Intensity	-	0.67	0.58	0.61	0.27
Bull/Bear Mkt regimes					
Bull Rel. Return	-	-6.01%	-4.08%	-9.60%	-13.12%
Bear Rel. Return	-	11.29%	8.58%	14.26%	14.45%
Low/High Vol. Mkt regimes					
Low Vol Rel. Return	-	-1.96%	-0.88%	-4.17%	-7.66%
High Vol Rel. Return	-	7.13%	5.52%	8.20%	7.83%
Bull/Bear Low Vol regimes					
Bull Regime	-	14.59%	11.77%	16.57%	14.41%
Bear Regime	-	5.33%	9.21%	0.91%	-0.32%

[7] *See the Scientific Beta white paper "Adding Value With Factor Indices: Sound Design Choices and Explicit Risk-Control Options Matter" for more details on factor investing approach.*
[8] *See the Scientific Beta white paper "A More Robust Defensive Offering" for more details on the construction of our defensive indexes.*

index. We emphasize that despite the relative protection vs. the cap-weighted index, all defensive solutions experience periods of high volatility, which might be close to 30%. Defensive indexes usually exhibit high market beta and high volatility in bear market regimes and inversely low market beta and low volatility in bull market regimes (see Exhibit 5). This might be clearly an undesirable property for investors seeking to be defensive not only relative to the cap-weight index but also in an absolute way. For these investors, a proper defensive solution should prevent the volatility from breaking through an upper level. In this setup, investors would be ensured to have a defensive solution in distressed times not only relative to the cap-weighted index but also in an absolute way.

EXHIBIT 2

One-year rolling volatility of SciBeta Defensive indexes and MSCI Minimum Volatility

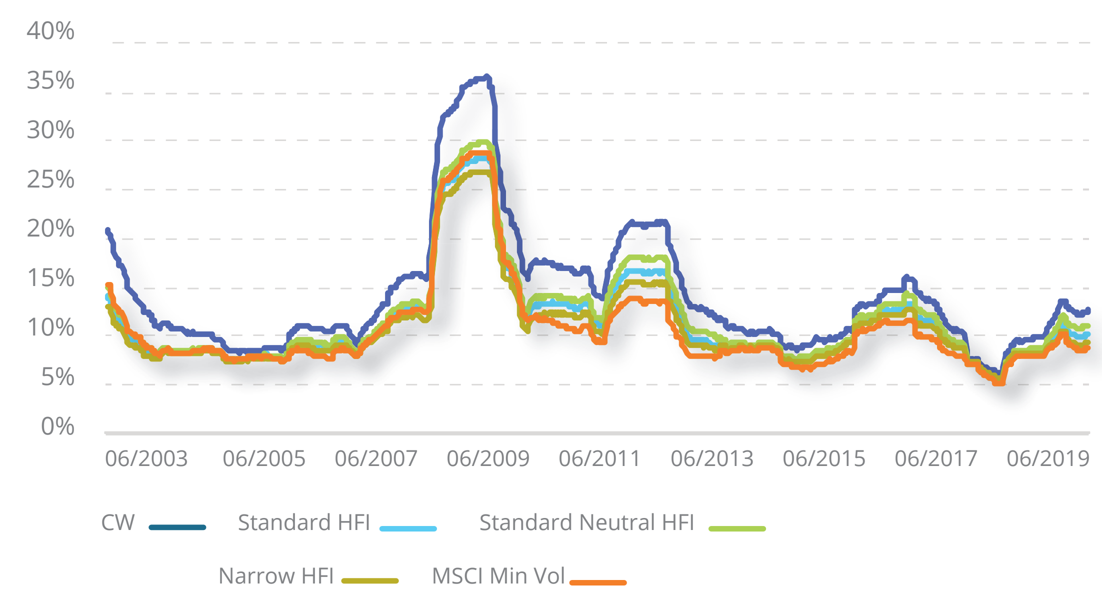
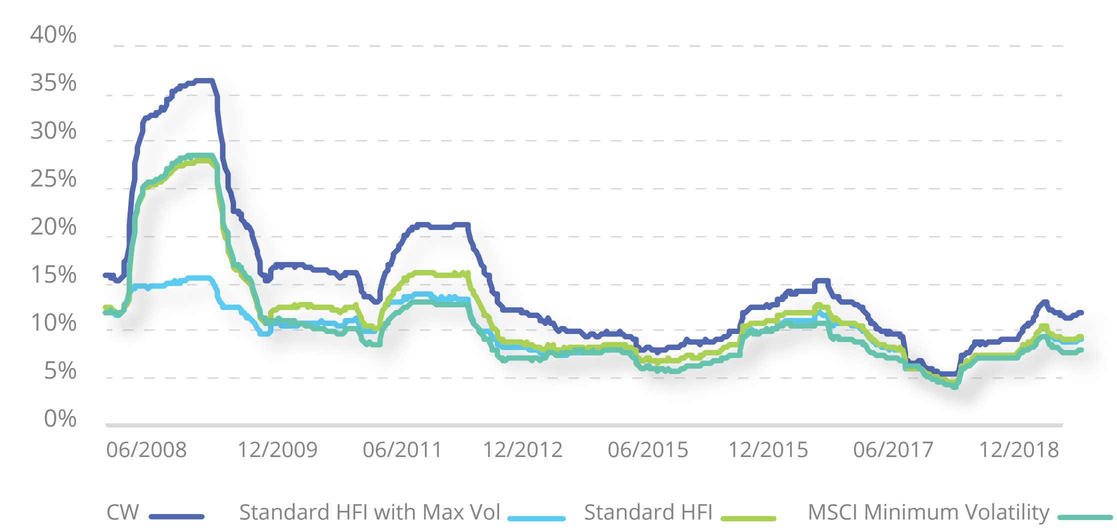


EXHIBIT 3

One-year rolling volatility of SciBeta Defensive indexes using the maximum volatility risk control option



A Maximum Volatility Risk Control Option to Design More Defensive Solutions

Scientific Beta offers a maximum-volatility risk-control option on its defensive indexes that allows the volatility to be capped at its historical level, which can be considered as a protection threshold. This is achieved through a dynamic allocation between the defensive index and cash on a monthly basis, where the maximum allocation to the index is constrained at 100%. In this setup, when forecasted volatility over the next month is below the historical volatility, then the solution is fully invested in the defensive index. When volatility over the following month is above the historical volatility, then the solution is invested simultaneously in the defensive index and cash. In this situation, the allocation to the defensive index is set as the ratio of historical volatility and forecasted volatility of the defensive index. In order to control turnover, we apply a buffer rule of 15%, which prevents the implementation of a new allocation if the absolute difference is below the buffer.

If we knew future volatility, this solution would be very effective and the maximum volatility cap would be always satisfied. Of course, in a real life application, this is not the case and we need to forecast volatility, which is an unknown variable. Hence, our maximum volatility risk control option relies on our ability to effectively forecast volatility. Our forecasting model is based on an asymmetric GARCH model that allows stylized characteristics of equity returns to be captured[9].

A good review of these concepts may be found in Jondeau and Rockinger (2006) and we briefly summarize them below:

i. Volatility clustering: Large changes in returns tend to be followed by similar large changes (of either sign), while small changes in returns tend to be followed by similar small changes. We observe volatility clustering from strong auto-correlations in square or absolute returns, while the return series itself tends to be only weakly auto-correlated;

ii. Fat-tail distribution: Equity returns are typically leptokurtic. In other words, they tend to display heavy return tails, implying a higher probability mass on extreme returns compared to a normal distribution;

iii. Asymmetry and leverage effect: The volatility response to a large positive return is typically smaller than the response to a large negative return. This asymmetry may be partly attributed to a leverage effect, because a decrease in a stock's price would result in a higher debt-to-equity ratio, and thus higher volatility of returns to the equity holders.

In Exhibit 3, we show the one-year rolling volatility of our maximum volatility risk control option on our standard HFI index, which is the flagship index of our defensive offering, as well as the standard HFI and MSCI Minimum Volatility indexes. We observe that the standard HFI index with the maximum volatility risk control option delivers a much more stable rolling volatility and provides a clear reduction of volatility in distressed times such as during the financial crisis of 2008 or the European crisis of 2011.

In Exhibit 4, we show the historical allocation to the standard HFI index. The average is 92%, but during the financial crisis of 2008, it dropped to 20%. Similarly, during the European Debt crisis of 2011, the allocation was only 40% to the defensive index. The annual one-way turnover of the dynamic allocation is 29%, which should be considered in addition to the turnover of the defensive indexes themselves, which remains limited (around 35%). This turnover is the direct cost of implementing the maximum volatility risk control option.

The main benefit of the maximum-volatility risk-control option is the improvement in conditionality. Indeed, Exhibit 5 reveals that volatility can be reduced substantially in both bear and high-volatility market regimes. In addition, we emphasize that the market beta is lower in bear market regimes and higher in bull market regimes, exactly opposite to the usual defensive indexes such as our standard HFI index or the MSCI Minimum Volatility index.

In Exhibit 6, we show some statistics on our standard HFI index with and without maximum volatility risk control option and on the MSCI Minimum Volatility index. The standard HFI index with maximum-volatility risk-control option allows a volatility reduction of 36% over the period compared to a 21% reduction without the risk control option. This translates into a Sharpe ratio of 0.72, which is

[9] *The model requires at least five years of daily data.*

The main benefit of the maximum-volatility risk-control option is the improvement in conditionality.

EXHIBIT 4

Historical allocation to the standard HFI index using the maximum volatility risk control option

EXHIBIT 5

Conditional Volatility and Market Beta in bull/bear and low/high volatility market regimes
The analysis is based on daily total returns in USD from June 30, 2007, to June 30, 2019. All statistics are annualized. Yield on Secondary U.S. Treasury Bills (3M) is used as a proxy for the risk-free rate. Bull (bear) market regimes are defined as months with positive (negative) market returns. Low (high) volatility market regimes are defined as 50% months with the lowest (highest) volatility. The smart factor indexes used are the SciBeta Developed High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy) with and without the maximum volatility risk control option and the MSCI World Minimum Volatility. The cap-weighted index is the SciBeta Developed Cap-Weighted.

June 30, 2007, to June 30, 2019 (RI/USD)	Standard HFI - Max Vol	Standard HFI	MSCI Min Vol
Bull Market - Volatility	8.08%	9.49%	8.93%
Bear Market - Volatility	13.35%	16.88%	15.87%
Bull Market - Beta	0.64	0.74	0.67
Bear Market - Beta	0.56	0.79	0.72
Low Vol Mkt - Volatility	6.98%	7.14%	6.43%
High Vol Mkt - Volatility	13.15%	16.86%	15.94%
Low Vol Mkt - Beta	0.78	0.80	0.66
High Vol Mkt - Beta	0.56	0.77	0.70

more than 150% higher than the cap-weighted index, 22% higher than the standard HFI index without the risk control option and 34% higher than the MSCI Minimum Volatility index. This strong defensiveness is confirmed with a market beta of 0.60. We emphasize that the characteristics of the standard HFI index are preserved despite the dilution induced by the average allocation of 92%, since exposure to the Low Volatility factor and overall factor intensity are still strong. Moreover, the factor intensity is still higher than MSCI Minimum Volatility index.

The maximum volatility risk control option has important conditional properties. First, relative returns in high-volatility market regimes are strongly improved. Second, the conditionality to bull/bear market regimes is reduced. Finally, our maximum risk control option good overall risk reduction is not due to an average under allocation to the standard HFI index, since a simple fix-mix strategy using the same average allocation to the defensive index as the maximum volatility solution delivers lower risk reduction and has worse conditional properties.

Which Defensive Index to Choose?

Scientific Beta offers a choice of defensive solutions based on low-volatility factor exposure. Importantly, while an index provider cannot replace the investor, as a passive solution provider they must allow the investor to implement investment strategies that correspond to their objectives and fiduciary constraints under the best possible conditions.

In the case of low-volatility indexes, we feel that the investor's main choice is whether the investment in the low-volatility index corresponds to a desire to collect the factor's risk premium or whether to protect their portfolio against deteriorating market conditions.

In the former case, the HFI low-volatility or the narrow low-volatility indexes provide very good exposure to the factor to varying degrees. Also, unlike many indexes that are available on the market, they also benefit from very good overall factor intensity and a very good level of diversification of systematic risk. Due to this good diversification and factor intensity, the Scientific Beta low-volatility indexes have better factor conditionality than the average competitor. While they benefit from the low-volatility risk premium when it is positive, they are also far less penalized when the same premium is negative.

In the latter case, it is obviously essential to be able to ensure that the defensive nature of the low-volatility index chosen is maintained when market conditions worsen. The Scientific Beta indexes that benefit from the maximum-volatility risk-control option provide this guarantee. Unlike traditional low-volatility indexes, the defensive nature of the HFI low-volatility maximum volatility indexes offered by Scientific Beta increases in situations of strong volatility or declining markets. •

EXHIBIT 6

Key statistics metrics of SciBeta Defensive offering and MSCI Minimum Volatility

The analysis is based on daily total returns in USD from June 30, 2007, to June 30, 2019. All statistics are annualized. Yield on Secondary U.S. Treasury Bills (3M) is used as a proxy for the risk-free rate. Bull (bear) market regimes are defined as months with positive (negative) market returns. Bull (Bear) Low Volatility regimes are defined as months with positive (negative) Low Volatility regressor returns. Low (High) volatility market regimes are defined as 50% months with the lowest (highest) volatility. Factor intensity is the sum of all non-market factor exposures. Regressions are performed using weekly returns. The smart factor indexes used are the SciBeta Developed High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy) with and without the maximum volatility risk control option and the MSCI World Minimum Volatility. The cap-weighted index is the SciBeta Developed Cap-Weighted.

June 30, 2007, to June 30, 2019 (RI/USD)	CW Index	Standard HFI - max vol	Sector Nuetral HFI - fix mix	Standard HFI	MSCI Min Vol
Ann. Returns	5.31%	8.10%	7.67%	8.29%	7.20%
Ann. Volatility	16.50%	10.55%	11.93%	12.97%	12.16%
Volatility Reduction	-	-36%	-28%	-21%	-26%
Sharpe Ratio	0.28	0.70	0.58	0.59	0.53
Sharpe Ratio Improvement	-	150%	109%	91%	109%
Market Beta	1.00	0.60	0.71	0.78	0.70
Exposure to Low Volatility	0.00	0.30	0.30	0.32	0.44
Factor Intensity	-	0.44	0.62	0.67	0.28
Bull/Bear Mkt regimes					
Bull Rel. Return	-	-12.46%	-11.61%	-8.15%	-15.93%
Bear Rel. Return	-	14.66%	13.09%	11.17%	16.26%
Low/High Vol. Mkt regimes					
Low Vol Rel. Return	-	-4.92%	-5.58%	-3.74%	-8.91%
High Vol Rel. Return	-	8.58%	8.33%	7.98%	10.25%
Bull/Bear Low Vol regimes					
Bull Return	-	13.84%	12.29%	13.34%	15.04%
Bear Return	-	-1.40%	-0.08%	-0.14%	-5.43%

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Integrating Macroeconomic Conditions Into Multi-Factor Allocation

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- **Returns of popular equity factors depend on macroeconomic conditions.**
- **Evenly balancing exposures across factors may not be enough to diversify macroeconomic risks.**
- **Accounting for macroeconomic risks allows investors to gain a better understanding of their risks exposures and helps them improve diversification of multi factor strategies.**

Despite their positive long-term premium, equity factors experience periods of substantial underperformance. This factor cyclicality is influenced by macroeconomic conditions. However, macro dependencies of popular factor strategies remain little documented by product providers. We propose a methodology for analyzing macroeconomic risk of equity factors, and show that ignoring such risks may lead to under-diversification of multi-factor portfolios.

Investors often balance portfolio weights across factors to diversify risk. Allocation techniques, such as risk parity, use information about average correlations across factors. Such approaches do not address the risk that two factors, which may have low correlation on average, may experience losses simultaneously if they have similar dependency on macroeconomic conditions. A better understanding of macroeconomic sensitivities will enable investors to improve diversification.

Investors often classify factors based on their dependency on market conditions in order to diversify across defensive and cyclical factors. However, stock market returns are a noisy measure of economic conditions, and conditioning on stock market cycles does not remove factors' sensitivity to macro conditions.[10] For example, let us consider the case of interest rates, which reflect a type of macroeconomic risk especially relevant for an investor who is also exposed to bonds.

Exhibit 1 shows that, irrespective of the prevailing stock market conditions, equity factors are highly dependent on interest rate surprises. Substantial performance differences arise within bull markets, and within bear markets, depending on interest rate conditions. The macro spreads, defined as the difference between annualized returns in times of high and low interest rate surprises, exceed a magnitude of 10% for several equity factors. Only conditioning on bull and bear markets thus does not capture the conditionality of factor returns.

Indeed, aggregate economic conditions beyond the stock market heavily affect investors. For example, a pension fund's contribution and liability stream depend on economic states, and asset classes other than equity play a role in the portfolio. Therefore, we need to go beyond equity market returns when defining economic conditions.

Identifying relevant macro variables

When it comes to analyzing macroeconomic dependencies, it is common practice to look at realized fundamental economic quantities. The growth in output and inflation rate are among the most widely used measures. Commonly used analytics rely on regressing factor returns on such variables. However, such an approach does not allow identifying a meaningful relationship between the factor premia and economic conditions, because asset prices react to changes in the economic environment well in advance.[11] Indeed, Exhibit 2 confirms that none of the

EXHIBIT 1

Dependency of factor returns on short-rate conditions within bull and bear markets
The table reports the differences between the annualized geometric mean returns of equity factors during the calendar months when innovations in short-term rates were in the highest vs. the lowest quartile. Bull (bear) markets are defined as quarters with a positive (negative) market return according to the CRSP value-weighted index. Significance based on Welch's t-test at the 10%, 5% and 1% levels are indicated by *, ** and ***, respectively. The results are based on monthly data from July 1963 to December 2017. Data source: K. French data library, AQR dataset, FED of St. Louis.

Economic states based on the short rate	Size	Value	Mom	Low Risk	Hi Prof	Low Inv
Macro spread in Bull Markets	2.2%	-3.1%	5.5%	-12.1%**	-0.9%	-1.7%
Macro spread in Bear Markets	6.5%	-19.6%**	-6.0%	-7.8%	-0.2%	-20.3%***

EXHIBIT 2

Factor premia vs. realized macro fundamentals
The table reports regression coefficients where independent variables are the seasonally adjusted real GDP growth and the consumer price index (CPI). Regressions are run using quarterly data, and statistical significance at the 10%, 5% and 1% levels is indicated by *, ** and ***, respectively. Data source: K. French data library, AQR dataset, FED of St. Louis.

Regression Betas	Size	Value	Mom	Low Risk	Hi Prof	Low Inv
Real Growth	0.25	0.04	0.64	-0.20	-0.33	-0.46
Inflation	0.15	0.64	0.85	0.03	-0.61*	0.38

[10] See Exhibit 9 of Amenc et al. (2019).
[11] The realized fundamental economic measures are "slow-moving" and are subject to post-publication revisions that make them a poor proxy for real-time expectations (see Runkle, 1998). Asset prices would usually react much faster to the changes in economic conditions (see Geske and Roll, 1983).

equity factors is significantly exposed to the contemporaneous growth in real GDP or inflation. Such simple regressions on macroeconomic realizations do not capture what drives factor returns.

Instead of relying on popular macro indicators, such as growth and inflation, we need to think carefully about which variables best capture the macroeconomic risks underlying factor cyclicality. However, given the large number of macro variables available, one should not fall into the trap of blindly testing all sorts of macroeconomic variables to try to establish a link with equity factors. Just like when we select equity factors, we need to apply some discipline when selecting macroeconomic drivers to analyze cyclicality. Without discipline, we could test an almost unlimited number of macro-variables with a high risk of finding spurious results. Ad hoc definitions of macro-factors in industry analysis have led to widely contradictory conclusions on the cyclicality of the main factors.[12]

We follow a stringent protocol to identify relevant state variables, drawing on well-established criteria in the finance and economics literature. We require that our candidate variables fulfill three conditions:

i. Reactiveness: The variable should be "fast-moving," responding quickly to the changes in expected economic conditions. We look at surprises in macroeconomic conditions rather than levels. Surprises are more suitable to establish a link with asset prices.
ii. Economic relevance: The variable should contain information about the outlook for economic activity. This implies that investors' expectations about aggre gate economic conditions are reflected in the variable.[13]
iii. Existing evidence: The link between the variable and equity factors should have been identified in the literature.[14] This requirement further reduces the risk of finding spurious links.

The following list shows our state variables[15], where we consider surprises rather than levels of each variable.[16]

In addition to empirical evidence, economic theory supports this choice of variables.[17] Exhibit 3 provides a brief summary of the economic rationale behind each variable. For example, the basic dividend discount model suggests that the aggregate dividend yield reflects the expected equity premium and future dividend growth in the economy. Amenc et al. (2019) go into the details of the proposed protocol for variable selection, and provide both empirical and economic justification that these macro variables are related to equity factors.

Macroeconomic Dependencies: Factors React to Macroeconomic Surprises

We analyze how six factors[18]—Size, Value, Momentum, Low Risk, Profitability and Investment — depend on the macro variables, using more than 55 years of U.S. data. Exhibit 4 reports the return spreads across macroeconomic conditions[19].

The sensitivities of factors to macroeconomic variables is both statistically significant and large in magnitude. For example, the macro spread of the investment and value factors in different short-rate conditions exceeds 7%, which is about twice as large as the unconditional average returns of these factors (3.2% and 3.7%, respectively). Investors looking to harvest the value or low investment premium should accept that in certain economic conditions, their factor-related performance will deviate by as much as what they will be earning on average.

The macroeconomic dependencies are in line with the economic mechanisms underlying different equity factors. The Value and Low Investment factors positively depend on the term spread. This is consistent with the finding that value firms have lower duration. The cash flows of value firms that have more assets in place are expected to occur earlier than those expected from growth firms. Similarly, firms that invest conservatively will expect cash flows nearer in the future, compared to the firms that invest aggressively. The negative dependency of the low risk factor on interest rates is also in line with the characterization of low risk stocks as "bond-like" (see Baker and Wurgler, 2012). The Low Risk factor performs considerably worse (by more than 10 percentage points) in times of positive interest rate surprises compared to negative surprises.

EXHIBIT 3

The list of macroeconomic state variables

Category	State Variable	Relation with economic conditions
Interest Rates	Short interest rates	- Reflects expected inflation, related to business cycle - Flight to quality reduces interest rate levels
	Term spread	- Reflects expectations on future rates and economic activity - Compensation for exposure to shocks on long-term discount rates
	Default spread	- Increasing spread adversely affects economic activity - Signals rising risk-aversion
Risk Compen-sation	Aggregate dividend yield	- Higher required return increases the yield
	Systematic volatility	- Can depress consumption and investment - Reflects uncertainty about equity prices
Illiquidity	Aggregate effective bid-ask spread	- Illiquidity is related to worsening macroeconomic outlook
	Aggregate price impact	- Flight to quality during bad times reduces liquidity of risky securities

The Impact of Macroeconomic Dependencies: The Case of a Bond Investor

Exhibit 4 shows that different factors reveal opposite sensitivities to a specific state variable. Economic sensitivities can be diversified, or at least diminished, if factors are combined suitably. By contrast, ignoring macroeconomic dependencies of factors may lead to poorly diversified portfolios.

Consider a bond investor who is already exposed to interest rate risk. The choice of factors will obviously have an impact on the total portfolio, as three out of six factors, namely Value, Low Risk and Low investment, are hurt by rising interest rates. However, the size, momentum and profitability factors have close to zero sensitivity to interest rate changes. The importance of choosing a suitable factor allocation is evident if we compare portfolios that invest only in rate-neutral or only in rate-sensitive factors.

Exhibit 5 highlights how the portfolios behave across different interest rate conditions. Adding the portfolio of rate-sensitive equity factors to bonds leads to a high macro spread of -31.2%. Popular allocations techniques, such as equal-weighted or equal-risk contribution, across all six factors leads to a spread of about 25%, while using the rate-neutral factor strategy leads to a macro spread of only -19.9%.

The reduction of conditionality achieved by rate-neutral factors translates into improved performance in the most adverse state for a bond investor, when there is a pronounced increase in short-term interest rates. Allocating to rate-neutral factors reduces losses by more than 60%, from -7.7% in the case when only bonds are held, down to -3%. When allocating to rate-sensitive factors, the loss in conditions when rates increase remains at -7.5%. Stark differences also appear when comparing extreme losses. Combining bonds with rate-sensitive equity factors leads to a drawdown of 43%, while combining bonds with rate-neutral equity factors leads to a drawdown of only 24%. Accounting for macroeconomic exposures clearly is relevant from a risk management perspective.

Towards managing macro risks

We now consider how multi-factor portfolios can achieve more balanced performance across different economic conditions. For illustration, we focus on interest rate surprises to define macroeconomic conditions. We obtain the theoretically optimal factor allocation that leads to the lowest possible dependency. An interesting feature of the resulting portfolio is that it shows the role of each factor in diversifying macroeconomic risk.

Exhibit 6 reports how the returns of macro-aware allocation behave in different short-rate conditions, and compare them to those of equal-weighted and equal-risk-contribution allocations. The results indicate that macro-aware

[12] See Amenc et al. (2019).
[13] See Boons (2016).
[14] See, e.g., Petkova (2006). For a list of reference, see Amenc et al. (2019).
[15] We use yield on three-month T-bills for the short-rate, 10-year minus one-year T-bonds for the term spread, Moody's Baa minus Aaa bonds for the default spread, 12-month trailing dividend yield on CRSP value-weighted index (NYSE/AMEX/NASDAQ), standard deviation of daily returns on CRSP index as a systematic volatility, the average effective bid-ask spread and illiquidity ratio as two aggregate illiquidity measures, adjusted for volatility-related component. For more details, see Amenc et al. (2019). Data is for the U.S.
[16] Innovations are estimated from a vector-autoregressive model as in Campbell (1996).
[17] See Amenc et al. (2019) for details.
[18] The data comes from the K. French website and AQR database (for Low Risk factor only).
[19] We report differences of annual returns during times when macro surprises were highest (top quartile) vs. lowest (bottom quartile).

EXHIBIT 4

Sensitivity of equity factors to macroeconomic surprises

The first panel of the table reports unconditional annualized geometric mean returns of six equity risk factors. The second panel reports macro spreads, defined as the difference between the annualized geometric mean returns of equity factors when innovations in state variables were in the highest and the lowest quartiles. Significance based on Welch's t-test at the 10%, 5% and 1% levels are indicated by *, ** and ***, respectively. The results are based on monthly data from July 1963 to December 2017. Data source: CRSP, K. French data library, AQR dataset, FED of St. Louis.

Economic states based on the short rate	Size	Value	Mom	Low Risk	Hi Prof	Low Inv
Unconditional Performance						
Annualized return	2.5%**	3.7%***	7.0%***	9.3%***	2.7%***	3.2%***
Macro Spreads						
Short rate	3.80%	**-8.4%***	1.40%	**-10.5%****	-0.60%	**-7.8%*****
Term spread	1.20%	**9.2%****	**-13.5%****	5.40%	**-5.6%***	**7.8%*****
Default spread	-5.30%	-0.10%	-2.00%	2.50%	**6.8%****	-1.80%
Dividend yield	4.30%	-5.90%	-6.10%	**-18.5%*****	**-14.8%*****	-3.50%
Effective spread	**11.1%****	0.10%	6.70%	4.50%	2.50%	-0.80%
Price impact	-3.00%	-0.30%	4.80%	0.10%	-1.90%	-2.60%
Systematic volatility	**-9.9%****	-6.80%	-4.90%	**-16.2%*****	1.80%	-4.60%

EXHIBIT 5

Understanding cyclicality matters for bond investors

The table reports unconditional and conditional performance measures of long-term bonds and its combinations with different equity multi-factor allocations. The bond premium is the difference between returns on CRSP 10-year bond index and one-month T-bills. The equal risk-contribution minimizes the deviation between the variance contribution of factors to that of a portfolio. The weights are constrained so that $(w^T w)^{-1} \geq 3$ and range between 1/18 and 1/2. The covariance matrix is estimated over the full sample. The results are based on monthly data from July 1963 to December 2017. Data source: CRSP, K. French data library, AQR dataset, FED of St. Louis.

		Bonds + Equity Factor Allocation			
Economic states based on the short rate	Bonds	Equal-Weighted	Equal Risk Contribution	Rate Sensitive Factors (EW)	Rate-neutral Factors (EW)
Unconditional Performance					
Return	1.9%	7.1%	6.4%	7.5%	6.5%
Volatility	7.6%	9.2%	8.8%	10.7%	9.9%
Sharpe ratio	0.24	0.78	0.73	0.70	0.65
Max drawdown	40.1%	27.1%	26.4%	43.3%	23.8%
Conditional Performance Based in Innovations in Short Rate					
Return when rates decrease	13.4%	20.4%	19.5%	23.7%	16.9%
Return when rates increase	**-7.7%**	**-5.1%**	**-5.1%**	**-7.5%**	**-3.0%**
P-value when rates increase	**< 1.0%**	**2.8%**	**2.3%**	**0.9%**	**31.3%**
Macro spread	-21.0%	-25.5%	-24.6%	-31.2%	-19.9%

EXHIBIT 6

Macroeconomic dependencies can be reduced

The table reports unconditional and conditional performance measures for different multi-factor allocation strategies. All statistics are annualized. The macro-aware and equal-risk contribution allocations are computed ex-post over the full sample, from July 1963 to December 2017. The weights are constrained so that $(w^T w)^{-1} \geq 3$ and range between 1/18 and 1/2. Data source: CRSP, K. French data library, AQR dataset, FED of St. Louis.

Economic state based on short rates	Macro-aware	Equal-weighted	Equal Risk Contribution
Unconditional return	3.8%	5.2%	4.5%
Return when rates decrease	3.8%	6.2%	5.5%
Return when rates increase	3.8%	2.7%	2.8%
Macro spread	**0.0%**	**3.6%**	**2.7%**

EXHIBIT 7

Factor weight of equity allocations

Economic states based on the short rate	Size	Value	Mom	Low Risk	Hi Prof	Low Inv
Macro-aware	**46.6% ↑**	**5.6% ↓**	**8.3% ↓**	**5.6% ↓**	**24.1% ↑**	**9.8% ↓**
Equal risk contribution	**21.6% ↑**	**13.6% ↓**	**11.6% ↓**	**10.0% ↓**	**24.2% ↑**	**19.0% ↑**

allocation reduces the macro spread to zero, compared to a spread of 3.6% for an equal-weighted portfolio and 2.7% for a risk parity portfolio. This is achieved by overweighting the size and profitability factors, and underweighting other factors, as shown in Exhibit 7. Size and profitability play an important role in diversifying away the interest rate risk inherent in the other factors.

While interest rate risk is a crucial issue for investors with heavy bond exposure, different investors may have a concern over other state variables. We can derive macro-aware factor allocations for any of the state variables in our analysis. For an average investor who is concerned with an All-Weather strategy, aggregating state variables into composite indicator that reflects aggregate economic conditions might be a more suitable approach. Amenc et al. (2019) propose several ways to combine individual variables into composite economic regimes, such as the macro outlook, risk tolerance and macroeconomic uncertainty. It is possible to construct an All-Regime allocation that minimizes the dependency across such regimes.

The proposed framework can be also used to analyze the diversification of a portfolio in different economic scenarios. For example, one can assume extreme shocks to the set of relevant state variables and estimate the possible impact on factor premia, or a portfolio, if such rare events occur. •

CONCLUSION

Our analysis shows that popular equity factors come with potentially strong dependencies on macroeconomic conditions. Standard allocation methods across different factors do not allow diversifying such business cycle risks. This may not be surprising, as such methods effectively ignore macroeconomic conditions in their design.

Though different investors may have different preferences in terms of desired dependencies, transparency about such risks should be an objective for investors and for the providers of factor products. Methodologies for documenting meaningful macroeconomic risks, such as the one used in this article, are readily available. Investors with exposure to value, momentum and other factors need to consider these macro dependencies more closely if they want to understand the risks they are exposed to.

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How to Add Value with Factor Indexes

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- **The performance of cap-weighted indexes suffers from a high concentration and a negative exposure to long-term-rewarded risk factors.**
- **To add value, factor indexes need to achieve both robust exposure to rewarded factors and good diversification of unrewarded risks.**
- **Investors need to consider implicit risks, such as sector and market risk, and make explicit choices about these risks.**

Resolving the Shortcomings of Cap-Weighted Indexes

Cap-weighted indexes are still the most prevalent passive investment instruments and widely used benchmarks in the asset management industry. However, they have two major disadvantages. First, they tend to be highly concentrated in the largest stocks from the investment universe. This concentration means that unrewarded or idiosyncratic risks are not completely diversified away, leaving the investor exposed to such risks. Second, they tend to have negative exposure to long-term-rewarded risk factors. For example, due to the concentration in large-cap stocks, which also tend to be stocks with a low book-to-market ratio, cap-weighted indexes have a negative exposure to the Size and Value factors.

Factor indexes aim to correct the issue with factor exposures, but often fail to address the problem of diversification. Smart factor indexes give investors an alternative that addresses both problems with cap-weighted indexes at the same time. To fully address the shortcomings of cap-weighted indexes, smart factor indexes need to both capture factor premia and improve diversification. This article gives an overview of how Scientific Beta designs smart factor indexes in order to achieve this goal.

Adding Value with Smart Index Design

Choosing robust factors

A crucial question in the design of factor indexes is the choice of the factors and their definitions. Scientific Beta uses the Size, Value, Momentum, Low Volatility, High Profitability and Low Investment factors.[20] There is strong empirical evidence that these factors deliver a premium. A key requirement for benefiting from these findings is to use the straightforward factor definition[21] that underlie this evidence. Constructing complex provider-specific factor definitions instead would de-connect factor indexes from the academic evidence, and expose investors to data-mining risk. Indeed, Harvey, Liu, and Zhu (2016) point out that one can find hundreds of "significant" factors when ignoring the risks of data mining.

Empirical evidence is only a necessary, but not a sufficient, condition for factor selection. We also need an economic rationale for the premia and their persistence. If a factor premium is driven by risk, some investors will be unwilling to take on exposure to the factor even if there is a long-term reward. Therefore, we only select factors with a solid risk-based explanation.

Exposure to the relevant factors can be implemented in a straightforward way by selecting 50% of the stocks in the universe based on their factor score.

Controlling factor interactions

Once the set of factors is defined, one should take into account the potential negative interaction effects between the factors. For example, a stock with a high Value score might have a low Momentum score. This can cause problems when combining Value and Momentum in a multi-factor portfolio, since the factor tilts will partly cancel each other.

Scientific Beta addresses this problem by applying a factor intensity filter in the stock selection process. This filter eliminates stocks with the lowest multi-factor scores. In the above example, this means that the Value stocks with the lowest Momentum score would be excluded. The intensity filter allows constructing multi-factor indexes from single-factor sleeves while still maintaining a strong factor intensity.[22] This approach can be used to derive customized allocations to multiple factors depending on investor objectives. Below, we focus on an equal-weighted allocation across the six single-factor indexes as a neutral starting point.

Diversifying specific risks

The Smart Beta 2.0 approach for constructing smart factor indexes (Amenc and Goltz, 2013) breaks down the index-construction process into two distinct steps. First, the investment universe is filtered according to the desired risk factor, as described above. Second, unrewarded idiosyncratic risks are diversified through a smart weighting scheme.

Several suitable weighting schemes exist that allow stock-specific risk to be diversified. When choosing a weighting scheme, the investor faces a trade-off between estimation risk and optimality risk. The former is the risk of measurement errors in the estimation of risk and return parameters. The latter is the risk that the approach is theoretically not optimal.

The risk of choosing a particular weighting scheme is not rewarded and can contribute to a lack of robustness in smart beta strategies (Amenc et al., 2015). Consequently, Scientific Beta uses the Diversified Multi-Strategy weighting scheme, which assigns equal weights to four different approaches[23] in order to diversify the optimality and estimation risks. As a result, each individual weighting scheme diversifies stock-specific risks and the combination of the four approaches diversifies the optimality or estimation risks inherent in a single weighting scheme. Diversifying across weighting schemes for a given factor is similar in spirit to diversifying across managers for a given investment style. The idea is to target a certain style (factor) while avoiding the manager-specific (weighting scheme-specific) risk.

Throughout the index design process, we apply mechanisms to ensure sufficient liquidity and to limit turnover (see Amenc, Bruno and Goltz (2019) for details).

Exhibit 1 provides evidence on the benefits of the Diversified Multi-Strategy weighting scheme together with the factor intensity filter presented above. These smart beta design features improve both the absolute and the relative performance. Tilting toward a set of rewarded risk factors without considering the index design improves the Sharpe ratio by around 27%, going from 0.40 to 0.51 or 0.52. However, the smart design features have an impact that is at least as big in our sample. Going from the factor tilted Cap-Weighted indexes to the Diversified Multi-Strategy indexes improves the Sharpe ratio by another 33%, to 0.68. The information ratio also improves strongly, from 0.42 to 0.56. This shows that index design is an important consideration that has a big potential to improve the performance of factor strategies.

Adding Value with Risk-Control Adjustments

Though investors benefit from investing in rewarded risk factors and improved diversification in the long term, factor-based indexes also carry a number of implicit risks that could significantly influence short-term performance. Factor index providers should document these risks, so that asset owners can make informed choices regarding them.

First, sector risk means that the sector allocation of an index deviates from the sector allocation of the cap-weighted benchmark. This increases the tracking error of a smart beta index and can materially affect its short-term performance. Scientific Beta offers investors the choice to opt for sector-neutral versions of its indexes to address these sector allocation mismatches (see Aguet,

[20] The corresponding academic studies are: Banz (1981) and Fama and French (1992) for Size; Fama and French (1992) for Value; Jegadeesh and Titman (1993) and Carhart (1997) for Momentum; Ang et al. (2006) for Volatility; Novy-Marx (2013) for High Profitability; and Hou, Xue, and Zhang (2015) for Low Investment.

[21] Factor scores, which are based on accounting data, can be difficult to compare across sectors. To make sure that the factor-based stock selections reflect economic realities rather than sector-specific accounting discrepancies, Scientific Beta performs the stock scoring by mega-sector for these factors. Our mega-sectors are Financials, Technology and Non-Financial Non-Technology firms.

[22] This is known as the "top-down" approach, as opposed to a "bottom-up" approach. We use this approach following Amenc et al. (2017), who show that it provides better performance per unit of factor exposure, due to better diversification.

[23] These weighting schemes are Maximum Deconcentration, Diversified Risk-Weighted, Maximum Decorrelation and Maximum Sharpe Ratio.

EXHIBIT 1

Performance of EDHEC-Risk Long-Term High-Factor-Intensity Diversified Multi-Strategy Smart Factor Indexes vs. Corresponding Cap-Weighted or Score-Weighted Factor Indexes

This exhibit shows the average performance and risk measures of the EDHEC-Risk Long-Term United States single-factor indexes, with various weighting schemes and with or without the application of the HFI filter. The analysis is based on daily total returns from Dec. 31, 1977, to Dec. 31, 2017. The stock universe is the EDHEC-Risk US LTTR universe. The cap-weighted index of all stocks in the universe is used as the benchmark. The three-month U.S. Treasury bill rate is used as the risk-free return. All statistics are annualized.

US LTTR Dec. 31, 1977, to Dec. 31, 2017	Broad CW	Average of Factor-Tilted CW Indexes	Average of Factor-Tilted Score-Weighted Indexes	Average of 6 HFI Diversified Multi-Strategy (4 Strategy Indexes)
Annualized Returns	11.62%	12.74%	12.83%	14.50%
Annualized Volatility	17.05%	15.64%	15.47%	14.39%
Sharpe Ratio	0.40	0.51	0.52	0.68
Annualized Relative Returns	-	1.12%	1.21%	2.88%
Annualized Tracking Error	-	2.63%	2.81%	5.10%
Information Ratio	-	0.42	0.43	0.56
Idiosyncratic Risk-Adjusted Return	-	-0.09	-0.09	0.10
Change in Specific Volatility	-	0.44%	0.44%	-0.08%

EXHIBIT 2

Performance and Risk Measures of High-Factor-Intensity Diversified Multi-Beta Multi-Strategy Indexes with Different Risk-Control Options

This exhibit shows the performance and risk measures of the EDHEC-Risk Long-Term United States High-Factor-Intensity Diversified Multi-Beta Multi-Strategy 6-Factor 4-Strategy EW index, both with and without sector neutrality and market beta adjustment. The analysis is based on daily total returns from Dec. 31, 1977, to Dec. 31, 2017. The stock universe is the EDHEC-Risk US LTTR universe. The cap-weighted index of all stocks in the universe is used as the benchmark. The three-month U.S. Treasury bill rate is used as the risk-free return. All statistics are annualized.

Dec. 31, 1977, to Dec. 31, 2017	Cap-Weighted Benchmark	HFI Div. MBMS 6F 4S EW	HFI Div. MBMS SN 6F 4S EW	HFI Div. MBMS 6F 4S EW MBA (Overlay)	HFI Div. MBMS SN 4S EW (Overlay)
Annualized Average Return	11.62%	14.50%	14.18%	15.47%	14.91%
Annualized Volatility	17.05%	14.38%	15.27%	17.73%	18.30%
Sharpe Ratio	0.40	0.68	0.62	0.61	0.56
P-Value	-	<0.1%	<0.1%	<0.1%	<0.1%
Maximum Drawdown	54.31%	48.13%	50.10%	55.26%	56.38%
Relative Return	-	2.88%	2.56%	3.84%	3.29%
Tracking Error	-	5.10%	3.96%	3.93%	3.57%
95% Tracking Error	-	9.79%	7.13%	7.60%	6.79%
Information Ratio	-	0.56	0.65	0.98	0.92
Max. Rel. Drawdown	-	32.95%	19.55%	20.40%	12.67%
Bull Rel. Return	-	0.28%	1.13%	5.44%	5.63%
Bear Rel. Return	-	6.75%	4.58%	1.18%	-0.41%
Factor Intensity	-	0.59	0.42	0.57	0.40

Amenc and Goltz (2018) for an in-depth discussion)[24].

Multi-factor indexes also tend to exhibit a relatively low market beta. The cost of under-exposure to the market is that an investor will not fully benefit from the market risk premium. It can also negatively affect conditional portfolio performance. During long bull markets, for example, indexes with market betas below one tend to underperform the cap-weighted market portfolio. The benefit of this under-exposure is that the portfolio has a defensive character and will suffer less from the market volatility. Given this trade-off, Scientific Beta believes that the investor should make an explicit choice regarding the level of market beta. We offer investors the option to adjust the market beta of our multi-factor indexes to one, depending on their preferences. Amenc, Goltz and Lodh (2018) describe our approach in more detail.

Exhibit 2 illustrates the trade-offs that exist when an investor has to make a choice regarding these risk-control options. Sector-neutrality and the market beta adjustment will result in a lower tracking error and a better overall relative performance with respect to the cap-weighted benchmark. The information ratio, for example, increases from 0.56 to 0.92 by applying both these risk controls. On the other hand, the options will come at the cost of a higher volatility and a lower factor intensity. In our sample, volatility rises from 14.38% to 18.30% and factor intensity decreases from 0.59 to 0.40.

24 Country risk is a similar form of implicit risk next to sector risk. Scientific Beta also offers investors the country-neutrality option to make an explicit choice regarding this source of risk.

To highlight the strong impact these risk control options can have on short-term performance, we show results for the most recent three years in Exhibit 3. Controlling sector and market beta risks has increased the average returns over this period from 11.57% to 14.50% in the U.S. universe and from 8.82% to 9.69% in the Developed ex-U.S. universe. In particular the market beta adjustment influenced performance strongly, as it allowed the strategies to capture the strong market performance to a full extent. As the table shows, choosing one's risk-control option can determine the difference between a positive or negative relative performance over the short term.

Of course, in times when equity markets face drawdowns, the opposite performance pattern would arise: strategies with market beta adjustment will tend to underperform unadjusted strategies, which maintain a defensive market beta. Over short horizons, non-factor risks will have a substantial impact on performance. While such non-factor risks are often left implicit in multi factor offerings, Scientific Beta allows investors to make an explicit choice on which risks they wish to control.

Sound Design Choices and Explicit Risk Control Options Matter

Smart factor indexes offer exposure to long-term well-rewarded risk factors, with strong empirical evidence and economic rationale. In addition to capturing exposure to factors, the indexes ensure a good reward for these exposures through diversification of unrewarded (specific) risk. Diversification allows long-term risk-adjusted performance to be improved while reducing short- and medium-term risk.

While non-factor risks are often implicit by-products of factor strategies, Scientific Beta's smart factor indexes enable investors to make explicit choices on risk control options. These options make it possible to respond to important fiduciary choices for investors or their asset managers. Additional options allow for seamless incorporation of Climate Change and ESG considerations into the Scientific Beta indexes. Moreover, smart factor indexes are widely used to implement risk allocation across factors to target investor specific risk-return objectives.

Such a wealth of choices is necessary to address each investor's objectives and constraints. A single optimal solution does not exist because investors are not identical after all. •

EXHIBIT 3

Performance and Risk Measures of High-Factor-Intensity Diversified Multi-Beta Multi-Strategy Indexes with Different Risk-Control Options over the past three years

This exhibit shows the performance and risk measures of the SciBeta United States High-Factor-Intensity Diversified Multi-Beta Multi-Strategy 6-Factor 4-Strategy EW index, both with and without sector neutrality and market beta adjustment. The analysis is based on daily total returns from June 30, 2016 to June 30, 2019. The stock universes are the SciBeta United States and SciBeta Developed ex-U.S. universes. The cap-weighted index of all stocks in the respective universes is used as the benchmark. The three-month U.S. Treasury bill rate is used as the risk-free return. All statistics are annualized.

June 30, 2016 to June 30, 2019	Cap-Weighted Benchmark	HFI Div. MBMS 6F 4S EW	HFI Div. MBMS SN 6F 4S EW	HFI Div. MBMS 6F 4S EW MBA (Overlay)	HFI Div. MBMS SN 4S EW (Overlay)
SciBeta US					
Annualized Average Return	14.38%	11.57%	13.16%	13.52%	14.50%
Annualized Volatility	12.27%	10.71%	11.45%	12.29%	12.58%
Sharpe Ratio	1.06	0.95	1.02	0.98	1.04
Relative Return	-	-2.80%	-1.22%	-0.85%	0.13%
Tracking Error	-	3.53%	2.81%	2.99%	2.61%
Information Ratio	-	NaN	NaN	NaN	0.05
SciBeta Developed Ex-US					
Annualized Average Return	9.57%	8.82%	8.72%	9.82%	9.69%
Annualized Volatility	9.58%	9.30%	9.33%	10.12%	10.13%
Sharpe Ratio	0.85	0.8	0.78	0.83	0.82
Relative Return	-	-0.75%	-0.85%	0.24%	0.12%
Tracking Error	-	2.13%	2.05%	2.08%	2.01%
Information Ratio	-	NaN	NaN	0.12	0.06

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Supporting the Transition to a Low Carbon Economy: the Scientific Beta Low Carbon Option

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- **Scientific Beta is introducing a Low Carbon fiduciary option that is applicable across its entire flagship offering of multi-factor indexes.**
- **This option enables investors to contribute to the transition to a low carbon economy, reduce the carbon footprint of their assets, and lower their exposure to climate change risks.**
- **This is achieved through negative screening of companies with significant coal involvement, positive screening with respect to carbon intensity, and a conditional adjustment mechanism in respect of index Weighted Average Carbon Intensity.**
- **These benefits are delivered while retaining the financial outperformance of the standard flagship indexes.**

Faced with the climate emergency, it is conservative to assume that there will be growing ecological, sociopolitical and economic pressure on governments to set and enforce climate policies that materially reduce the gap between current emissions and the levels required to mitigate climate change. For most companies, this political response is a major component of the risks of a transition to a low carbon economy, which also include the impact from evolving technology, social norms and consumer behavior. These risks could materially affect the financial positions of companies through balance sheet and income statement effects.

Thus, while ethical and socially responsible investors should be expected to orient their investments, engagement and outreach policies to contribute to the fight against climate change, all investors need to consider the possible financial impacts of climate change on their portfolios.

Against this backdrop, Scientific Beta is introducing a Low Carbon fiduciary option that is applicable across its entire flagship offering of multi-factor indexes. It addresses the three most common decarbonization objectives for investors:

1. Contributing to the transition to a low carbon economy;
2. Reducing the "carbon footprint" of investments;
3. Reducing exposure to climate change risks.

These objectives are achieved with three approaches to decarbonization:

- Negative screening ensures divestment from companies with strong coal involvement. This acknowledges that phasing out coal is a priority in transition scenarios due to its importance and environmental inefficiency and that coal assets are thus at a particular risk of becoming stranded in the transition.
- Positive screening targets the companies with the highest emissions per unit of revenues (carbon intensity) across sectors. This acknowledges that the demands of the transition extend beyond shedding coal dependency and that transition risk is pervasive. Screening is region neutral and strikes a balance between exclusion efficiency and sector protection, while upholding best-in-class selection within each affected sector.
- A conditional adjustment mechanism reduces the potential shortfall between the quarterly level of the index Weighted Average Carbon Intensity (WACI) and a desired long-term reference level. This acknowledges that guaranteeing a high reduction in the metric favored by the Taskforce on Climate-related Financial Disclosures (TCFD) protects the long-term decarbonization strategy against potential challenges from short-term deviations.

The application of the Low Carbon option produces a drastic reduction in allocation to coal assets and to the most carbon-intensive companies. This incentivizes the transition of shunned and other companies towards more sustainable activities and technologies. It also contributes to material reductions in both carbon footprints — i.e., measures of the portfolio's indirect contribution to emissions — and exposures to the companies most liable to be affected by transition risks. Over the last 10 years, the average index WACI is about half that of the benchmark on developed markets.

Decarbonization is delivered without compromising the financial outperformance of the standard flagship indexes.

ESG Incorporation Philosophy, ESG Screens and Decarbonization Approaches

Scientific Beta ESG Incorporation Philosophy

Scientific Beta's Environmental, Social and Governance (ESG) incorporation philosophy centers on exclusions that are determined solely on ESG merits and applied as the first step in index construction.

This approach respects the principles of socially responsible investors and, as a result, exclusions send clear signals to issuers and are straightforward to explain to stakeholders. From an ESG risk management point of view, the approach targets companies whose performance fails to meet standards. Designed in this framework, the

EXHIBIT 1

Coal Involvement Filter

Type of involvement	Scope	Threshold
Ownership of coal reserves	All companies except those classified in the Iron and Steel industry	No tolerance
Coal mining, support and wholesaling	- All companies classified in the Coal industry - All companies with significant revenues from thermal coal irrespective of their industry and sector classification	No tolerance 30% of total revenues
Coal in power generation fuel mix	All power generating companies classified in the Utilities or Financial sectors	30% of power generation capacity

Low Carbon option demonstrates unambiguous support for the transition to a low carbon economy and reduces index exposure to transition risks. Divestment from companies involved with particularly inefficient fuels or high carbon intensity contributes to increasing their cost of capital and incentivizes transition by these companies and others. Reduced exposure to companies whose assets face high risks of stranding or with high potential exposure to overall transition risks promotes index resilience to climate change.

In the absence of sound academic evidence documenting the existence of non-redundant ESG performance factors, dealing with ESG concerns as a first step allows downstream index construction to concentrate on the rewarded systematic risks through factor-based security selection and the mitigation of conventional risks through diversification weighting and risk controls.

Coal Involvement Filter and other Negative ESG Screens

The Low Carbon fiduciary option includes a coal involvement filter that is part of the set of core ESG screens embedded in all of Scientific Beta's off-the-shelf ESG options. Quantitatively, the bulk of the exclusions, as per these negative screens, is in respect of coal involvement as defined in Exhibit 1.

From an ethical and socially responsible investment standpoint, the focus on coal is mandated by it being the largest source of electricity and the fuel with the lowest heating value normalized by greenhouse gas emissions. Divestment of companies with a major role in the supply and demand for coal is consistent with a deontological approach and sends a clear signal to stakeholders.

From the point of view of potential financial materiality of ESG risks, coal-mining and coal usage, especially for energy production, need to be drastically curtailed. If the transition is faster or more severe than the current baseline scenarios, the book value and/or the earning potential of coal assets will be impaired. If such impairments are not correctly anticipated by investors, coal companies will be repriced. Mitigating this risk of stranding provides a financial motive for divestment.

The other negative screens cover companies that entail risks of association with serious violations of fundamental norms, notably in reference to the human rights, labor, environment and anti-corruption norms underlying the United Nations Global Compact. Companies that deny investor oversight by issuing only non-voting shares are also excluded in reference to the OECD Principles of Corporate Governance. Product-based exclusions, other than in respect of coal involvement, target companies with involvement in anti-personnel landmines and cluster bombs and tobacco-industry companies and manufacturers of tobacco products; companies with such involvements are not eligible to be recognized as participants in the United Nations Global Compact.

Removing companies that fall short of global standards of responsible business conduct and corporate governance or that are involved in activities that conflict with global ESG norms or their objectives ensures that the pursuit of decarbonization and financial performance does not harm the respect of ESG norms.

Positive Exclusion of High-Carbon-Intensity Companies

The second decarbonization approach implements a region-neutral flexible best-in-class filter that excludes companies with high carbon emissions to revenues while protecting sector representation. Both direct corporate emissions and indirect emissions from the generation of electricity, steam, heating or cooling purchased or consumed by the company are included (Scope 1 and 2 emissions, respectively). Data quality in respect of other indirect emissions remains insufficiently granular to support stock-level decisions (but we include these Scope 3 emissions in reporting).

The filter ranks constituents in each region according to company level carbon intensity and exclusion proceeds strictly from worst to best subject to sector rules, notably a 50% cap in the number of exclusions. Relative to a sector-neutral approach, the filter promotes materially higher impact for a given exclusion budget. This budget is set at 10% of the number of securities in each region.

From a non-financial point of view, this second approach to decarbonization recognizes that the transition to a low carbon economy goes beyond phasing out thermal coal and that carbon efficiency should be incentivized in key sectors and beyond. From the point of view of ESG risks with potential financial materiality, it acknowledges that transition risk pervades key transition sectors, e.g., Energy–Fossil Fuels, Utilities, Basic Materials (sch as steel and cement), Transportation, and Real Estate, and affects high-carbon-intensity companies across all sectors.

Weighted Average Carbon Intensity Assurance

The coal involvement and carbon intensity filters jointly remove the companies most exposed to transition risks from any derived index and promote improved index-wide average carbon metrics. In keeping with the ESG incorporation philosophy, however, the latter are by-products of the screening and index construction methodology rather than objectives or constraints determining individual security selection and weighting.

To protect index strategies against questioning in respect of adverse short-term deviations of carbon metrics, the Low Carbon fiduciary option embeds a conditional shortfall reduction mechanism. The mechanism is triggered when the WACI of the index at rebalancing fails to achieve a reduction of 35% relative to the benchmark and targets a reduction of 40% by minute sector-weight adjustments. The trigger threshold was calibrated historically to ensure that activation would remain rare and adjustments are highly constrained to preserve the financial characteristics of the index.

Risks and Performances of Low Carbon Multi-Smart-Factor Indexes

In this section, we study the impact of the Low Carbon option on the ESG and financial risks and performances of the flagship Multi-Beta Multi-Strategy High Factor Intensity 6-Factor 4-Strategy EW index with and without sector control. ESG data is availed from Institutional Shareholder Services and public sources.

Decarbonization Performance

In assessing decarbonization, we consider both exposure to assets with high transition relevance and stranding risk potential and overall portfolio metrics.

As shown in Exhibit 2, filtering leads to indexes in which pure coal players are removed and exposure to companies with majority turnover from fossil fuels is reduced.

As shown in Exhibit 3, filtering leads to a dramatic fall in exposure to coal reserves, as measured by their potential carbon dioxide emissions normalized by investment.

Exhibit 4 documents that the Low Carbon option reduces exposure to the transition risks associated with power generation by reducing the power generation capacity controlled and improving its WACI, notably by tilting the fuel mix away from coal.

Exhibit 5 shows carbon metrics that the TCFD considers of interest for reporting. Carbon Footprint and Carbon Intensity inform on responsibility as they allocate corporate emissions to the portfolio in respect of the share of capital controlled (and then normalize owned emissions

EXHIBIT 2

Fossil Fuel Sector Exposure for Various Indexes, Developed Universe, Five-year Averages

Fossil Fuel Involvement Metrics – CWI relativeScientific Beta Developed Universe, 20 quarter average at December 2018	Standard Capitalization Weighted Index	MBMS HFI 6F EW		MBMS HFI 6F EW Sector Neutral	
		Standard	Low Carbon option	Standard	Low Carbon option
Companies classified in the Energy - Fossil Fuels Sector (TRBC5010)	6.76%	-27%	-37%	+8%	0%
Of which in the Coal Industry Group	0.05%	-48%	-100%	+89%	-100%
Of which in the Oil & Gas Industry Groups	5.46%	-19%	-28%	+22%	+14%
Companies with 25-50% of their turnover from Fossil Fuels	1.66%	+44%	+6%	+5%	+17%
Companies with 50% and more of their turnover from Fossil Fuels	8.69%	+12%	-35%	-1%	-13%

EXHIBIT 3

Potential Emissions Associated with Reserves, Various Indexes, Developed Universe, December 2018

Reserved Emissions – CWI relative Scientific Beta Developed Universe, December 2018	Standard Capitalization Weighted Index	MBMS HFI 6F EW		MBMS HFI 6F EW Sector Neutral	
		Standard	Low Carbon option	Standard	Low Carbon option
Potential Emissions (CO_2 Mtons per USD1bn)	2.503	+29%	-66%	+20%	-49%
Of which from Coal reserves	1.192	+68%	-96%	+23%	-97%
Of which from Oil & Gas reserves	1.310	-6%	-39%	+18%	-6%

EXHIBIT 4

Exposure to Power-Generating Utilities for Various Indexes, Developed Universe, End of 2018

Power-generating Utilities metrics – CWI relative Scientific Beta Developed Universe, December 2018	Standard Capitalization Weighted Index	MBMS HFI 6F EW		MBMS HFI 6F EW Sector Neutral	
		Standard	Low Carbon option	Standard	Low Carbon option
Brown share	57.59%	+6%	-7%	+1%	-9%
Coal	21.59%	+43%	-42%	+15%	-46%
Gas	30.61%	-13%	+9%	-8%	+10%
Oil	5.39%	-37%	+42%	-12%	+28%
Renewables	24.28%	-22%	+3%	-9%	+20%
Nuclear	15.25%	+16%	+31%	+11%	+17%
Others	2.88%	-15%	-52%	+2%	-78%
Controlled Power Generation Capacity (MW) per USD1M invested	28.18	+126%	-37%	+37%	-38%
Weight of analyzed utilities	3.84%	+115%	-27%	+14%	-24%
WACI of analyzed utilities	2,324	+33%	-61%	+33%	-61%

EXHIBIT 5

TCFD Carbon Metrics for Various Indexes, Developed Universe, 10-year Averages

Standard Carbon Metrics – CWI relative Scientific Beta Developed Universe, 40 quarter average at December 2018	CWI	MBMS HFI 6F EW		MBMS HFI 6F EW Sector Neutral	
	Standard	Standard	Low Carbon option	Standard	Low Carbon option
Weighted Average Carbon Intensity (Scopes 1+2 tons / USD M)	216	+57%	-54%	+15%	-51%
WACI (Scopes 1+2+3)	849	+22%	-56%	+10%	-46%
Carbon Intensity (S1+2 tons / USD M)	241	+13%	-61%	-6%	-55%
Carbon Intensity (Scopes 1+2+3)	896	-4%	-55%	-6%	-42%
Carbon Footprint (S1+2 k tons / USD bn)	201	+33%	-55%	+10%	-48%
Carbon Footprint (Scopes 1+2+3)	738	+13%	-48%	+10%	-32%
Carbon-related Assets	11.18%	-9%	-42%	+1%	-10%
WACI of Carbon-related Assets	912	+90%	-34%	+10%	-48%

EXHIBIT 6

Factor Exposures in CAPM and 7-Factor Model for Various Indexes, Developed Universe, 10 years

Factor Exposures Metrics – Regressions Based AnalysesScientific Beta Developed Universe, 10 years ended December 2018	MBMS HFI 6F EW		MBMS HFI 6F EW Sector Neutral	
	Standard	Low Carbon option	Standard	Low Carbon option
CAPM Alpha	**3.40%**	**3.64%**	**2.84%**	**2.88%**
CAPM Beta	**0.84**	**0.84**	**0.87**	**0.87**
CAPM R Squared	96.73%	96.67%	97.77%	97.52%
Seven-Factor Alpha	0.52%	0.50%	0.82%	0.54%
Market Beta	0.85	0.85	0.88	0.87
SMB* Beta	0.15	0.15	0.14	0.14
HML* Beta	0.07	0.06	0.08	0.07
MOM* Beta	0.08	0.08	0.08	0.08
Low Vol* Beta	0.17	0.13	0.11	0.11
High Prof* Beta	0.14	0.23	0.11	0.16
Low Inv* Beta	0.05	0.07	0.02	0.02
Seven-Factor R Sqrd	98.21%	98.14%	98.45%	98.32%
Factor Intensity	0.67	0.73	0.53	0.57

EXHIBIT 7

Number of Constituents and Deconcentration of Various Indexes, Developed Universe, December 2018

Number of Constituents and Deconcentration Scientific Beta Developed Universe, December 2018	Standard Capitalization Weighted Index	MBMS HFI 6F EW		MBMS HFI 6F EW Sector Neutral	
		Standard	Low Carbon option	Standard	Low Carbon option
Number of Constituents	1,467	901	795	925	803
Effective Number of Constituents	276	502	438	389	334

by portfolio value and owned revenues, respectively). WACI and Carbon-related Assets measure exposure to carbon-intensive companies and sectors. The exhibit documents that the Low Carbon option has historically produced indexes with excellent decarbonization assessed from both responsibility and risk-exposure angles.

Financial Risks and Performance

Exhibit 6 presents factor analysis of index performance with and without application of the Low Carbon option and shows that filtering does not reduce the potential for adding value with common factor tilts.

Exhibit 7 shows that despite the reduction in the number of constituents linked to exclusions, Low Carbon indexes remain significantly more deconcentrated than the benchmark, leaving good potential for adding value through diversification of idiosyncratic risk.

Finally, Exhibit 8 shows that the Low Carbon version of the multi-smart factor index slightly outperforms its unfiltered counterpart over 10 years but that this advantage disappears if sector biases are controlled. •

EXHIBIT 8

Performance, Risk-Adjusted Performance and Conditionality of Various Indexes, Developed Universe, 10 years

Scientific Beta Developed Universe 10-year performance to end 2018	Standard Capitalization Weighted Index	MBMS HFI 6F EW		MBMS HFI 6F EW Sector Neutral	
		Standard	Low Carbon option	Standard	Low Carbon option
Annualized Returns	10.10%	12.30%	12.60%	12.03%	12.02%
Annualized Volatility	14.34%	12.42%	12.52%	12.84%	12.80%
Sharpe Ratio	0.68	0.96	0.98	0.91	0.91
Maximum Drawdown	26.51%	22.84%	22.29%	22.66%	22.39%
Annualized Relative Returns	-	2.19%	2.49%	1.93%	1.92%
Annualized Tracking Error	-	3.01%	2.97%	2.48%	2.58%
Information Ratio	-	0.73	0.84	0.78	0.74
Historical Prob. of Outperformance (1Y)	-	76.88%	80.20%	84.89%	84.16%
Historical Prob. of Outperformance (3Y)	-	99.13%	97.21%	100.00%	100.00%
Historical Prob. of Outperformance (5Y)	-	100.00%	100.00%	100.00%	100.00%
Bull-market Relative Return	-	-3.68%	-2.73%	-2.44%	-2.44%
Bear-market Relative Return	-	7.27%	6.91%	5.61%	5.58%

CONCLUSION

The Low Carbon fiduciary option applicable across Scientific Beta's flagship offering allows ethical and socially responsible investors to dissociate from companies with significant coal involvement and further promote the transition to a low carbon economy by reorienting investments toward less carbon-intensive activities and companies. The application of the option produces material reductions in the coal-asset exposure of derived indexes and in the indirect contribution of these indexes to climate change. Since it relies on an approach that determines potential inclusion in derived indexes based solely on the coal involvement of each firm and its carbon intensity relative to peers, the Low Carbon fiduciary option sends clear signals to issuers regarding the urgency of decarbonizing their operations and is straightforward to explain to beneficiaries, clients and other stakeholders.

By delivering a drastic reduction of exposure both to coal assets and to the most carbon-intensive companies, the Low Carbon fiduciary option produces derived indexes with higher resilience to transition risks relative not only to standard multi-factor indexes but also to parent universe benchmarks. Derived indexes also boast benchmark-relative reductions in respect of Weighted Average Carbon Intensity, the carbon exposure metric recommended by the Taskforce on Climate-related Financial Disclosures for reporting by asset managers and asset owners, of circa 50% over the last 10 years. As such, they are also particularly relevant for investors who wish to implement multi-factor investment strategies but recognize that climate change risks may materially impact portfolio values and wish to apply ambitious mitigation of these risks as a precaution.

Over the last 10 years, the multi-factor indexes to which the Low Carbon fiduciary option has been applied are found to protect the sources of financial outperformance of the Scientific Beta multi smart-factor offering and typically perform in line with their unfiltered counterparts. Supporting the transition to a low-carbon economy and protecting against the risks of this transition had no meaningful impact on financial performance.

Upholding Global Norms and Protecting Multi-Factor Indexes Against ESG Risks: the Scientific Beta ESG Option

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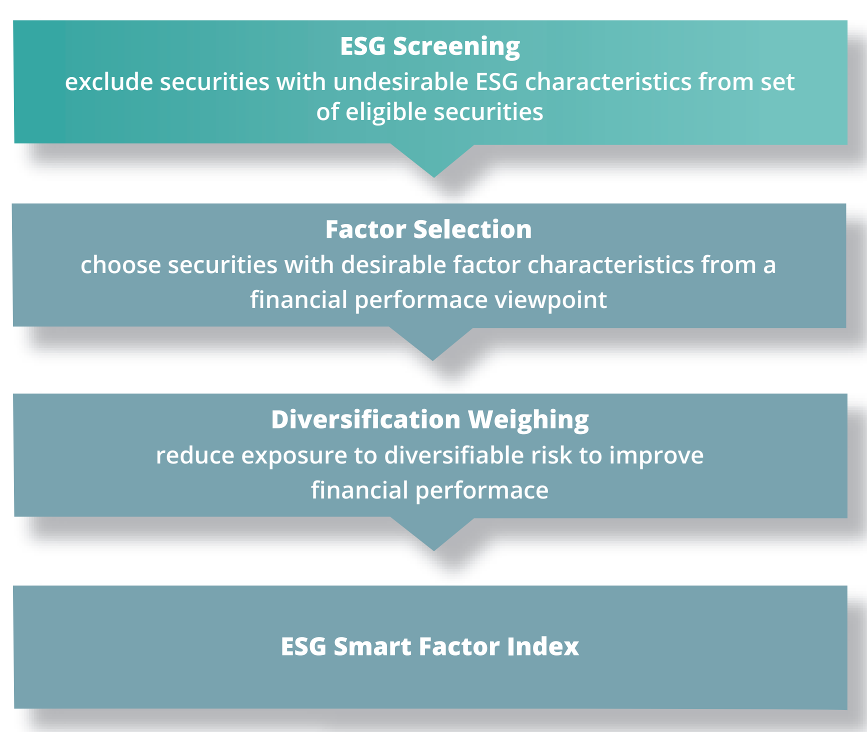
- **Scientific Beta is introducing an ESG fiduciary option that is applicable across its entire flagship offering of multi-factor indexes.**
- **This option implements negative screening grounded in global norms and corresponding to consensus themes. Product exclusions target companies with involvement in controversial weapons, tobacco production and coal while conduct exclusions concern companies with implications in critical ESG controversies and companies that flout basic standards of corporate governance by denying oversight to investors.**
- **This option is relevant to investors who wish to dissociate from controversial companies, demonstrate support of global norms, mitigate reputational and liability risks or avoid ESG risks with potential adverse financial materiality.**
- **These benefits are delivered while retaining the financial outperformance of the standard flagship indexes.**

EXHIBIT 1

Overview of ESG-Smart-Factor Index Construction Steps



Business-case investors incorporating Environmental, Social and Governance (ESG) dimensions with a view to strengthening risk management or enhancing returns are joining traditional values-based and socially responsible investors incorporating non-financial dimensions into investment to uphold personal values or social norms, and/or seek positive ESG impact.

Scientific Beta recognizes the diversity of these motivations and offers an ESG fiduciary option that is applicable across its entire flagship offering of multi-factor indexes. Implementing exclusionary screening grounded in international norms, it is simple, transparent and consensus and addresses the ESG incorporation needs of diverse investors.

Exclusions may be motivated by a deontological imperative to dissociate from unethical products and conducts or by a consequentialist approach seeking to bring about positive change by incentivizing ethical behavior or transition toward responsible activities on the part of shunned and other companies. Exclusions may also be motivated by self-interest to the extent that they reduce the reputational and liability risks involved with supporting companies and activities that fail global standards and remove companies whose ESG characteristics entail a risk of material negative impact on the financial performance of the portfolio. This includes companies that could be most negatively affected by ESG-related systematic changes owing to their controversial activities, as well as those that could be especially prone to future idiosyncratic value-destroying ESG events and controversies owing to their past and current controversial behavior.

In the rest of this article, we describe our ESG integration approach, review the global norms supporting the ESG fiduciary option and detail its screens. We conclude with a presentation of the impact of the ESG fiduciary option on the ESG and financial risks and performances of the flagship Multi-Beta Multi-Strategy High Factor Intensity 6 Factor 4 Strategy EW index with and without sector control.

Incorporating Environmental, Social and Governance Dimensions into Investment

As shown in Exhibit 1, Scientific Beta's ESG incorporation philosophy centers on exclusions that are determined solely by ESG merits as the first step in index construction. As a result, exclusions send clear signals to issuers and are straightforward to explain to stakeholders. By promoting an increase in the cost of capital through reduced demand for securities and increased uncertainty, exclusions may curtail the growth of harmful companies. The approach respects the deontological considerations of ethical investors and the promotion of positive change sought by socially responsible investors.

To the extent that the poor ESG performances of targeted securities entail distinctive ESG risks to the investor or its portfolio, the approach has risk-management relevance to self-interested investors. Dealing with ESG concerns as a first step also allows downstream index construction to concentrate on exploiting rewarded systematic risks through factor-based security selection and mitigating unrewarded risks through diversification weighting and risk controls. In this way, the financial performance of the index is not predicated on the financial materiality of ESG data. In the absence of sound academic evidence documenting the existence of non-redundant ESG performance factors and given the exploratory nature of work using ESG data to improve risk estimates, this approach is conservative.

This ESG incorporation philosophy is in stark contrast with integrated ESG approaches that allow for compensation between ESG and financial characteristics at the security level and/or approaches that define ESG performance as a portfolio average and allow a higher allocation to ESG leaders to make up for a higher allocation to ESG laggards. Exclusions based on composites of ESG and financial performance convey mixed signals to issuers and may be interpreted as ESG-washing by the public. Approaches driven by average ESG scores at the portfolio level assume that the utility of ESG performance is linear, which is not borne out by observation and is inconsistent with controversy risk aversion. Such approaches also assume that the risks that ESG scores may proxy are linear, which is not a conservative approach for downside risk management. Finally, from a traditional bottom-line perspective, approaches based on composites of ESG metrics and traditional financial signals lack theoretical support and may reduce control over time-tested sources of risk-adjusted performance.

Upholding Global Norms – A Review of ESG Fiduciary Option Screens

The Relevance of Filtering in Relation to Norms

Exclusionary screening, also known as negative screening, involves the exclusion of certain countries, sectors or companies involved in activities deemed unacceptable or controversial. This is the oldest approach to responsible investment and remains the most practiced globally in asset terms. Negative screening is easy to explain to stakeholders and, contrary to positive or best-in-class screening based on ratings, it strictly guarantees the exclusion of entities that are known to violate minimum standards.

The responsible investment approach known as norms-based screening involves the screening of investments based on compliance with international norms. These norms may pertain to certain prohibited or restricted activities or to standards of responsible business conduct. Exclusionary screening in relation to norms may go beyond excluding companies violating norms and target companies whose activities are fundamentally at odds with the ESG objectives pursued by global norms.

Filtering in relation to norms can be relevant for different types of investors, as described in Exhibit 2.

ESG Fiduciary Option Screens

The screens implemented by the ESG fiduciary option encompass conduct-based exclusions in respect of violations of fundamental norms of responsible business conduct and corporate governance and product-based exclusions in respect of involvement in controversial weapons, tobacco and coal.

Responsible business conduct

Responsible business conduct entails compliance with applicable laws and internationally recognized standards of appropriate behavior. Launched in 2000, the United Nations Global Compact has become the world's largest voluntary corporate responsibility initiative. It promotes alignment of businesses with 10 principles in the areas of human rights, labor, environment and anticorruption derived from global norms (as presented in Exhibit 3).

The ESG fiduciary option includes a filter screening out companies facing critical controversies in relation to their fundamental responsibilities in the four areas covered by the Global Compact. This filter relies on data provided by Vigeo-Eiris.

EXHIBIT 2

Relevance of norm-based exclusions for different types of investors

Values-based Investor	Dissociate from investments that contravene global norms
Socially Responsible Investor	Incentivize the respect of global norms for the common good
Traditional Investor	Avoid the reputational and liability risk involved with an investment policy that allows investment in companies contravening global norms Avoid exposure to investments whose risk-adjusted returns could disappoint as a result of materialization of high ESG risks For a universal owner, promote the reduction of negative externalities that are financially detrimental to the portfolio

EXHIBIT 3

The Ten Principles of the United Nations Global Compact (UN, 2019)

Area and Global Norm of Reference	Principle
Human Rights Universal Declaration of Human Rights	1: Businesses should support and respect the protection of internationally proclaimed human rights 2: Make sure that they are not complicit in human rights abuses.
Labor International Labor Organization's Declaration on Fundamental Principles and Rights at Work	3: Businesses should uphold the freedom of association and the effective recognition of the right to collective bargaining; 4: The elimination of all forms of forced and compulsory labor; 5: The effective abolition of child labor; 6: The elimination of discrimination in respect of employment and occupation.
Environment Declaration on Environment and Development	7: Businesses should support a precautionary approach to environmental challenges; 8: Undertake initiatives to promote greater environmental responsibility; 9: Encourage the development and diffusion of environmentally friendly technologies.
Anti-Corruption United Nations Convention Against Corruption	10: Businesses should work against corruption in all its forms, including extortion and bribery.

EXHIBIT 4

Involvement in Controversial Products/Activities and Conducts for Various Indexes, Developed Universe, December 2018

Cumulated weights of companies with involvement (December 2018) Scientific Beta Developed Universe	Cap-weighted Index	MBMS HFI 6F EW		MBMS HFI 6F EW Sector Neutral	
		Standard	ESG option	Standard	ESG option
Controversial Weapons Involvement					
All controversial weapons	**2.53%**	1.58%	0.00%	2.02%	0.00%
Tobacco involvement					
Tobacco companies and producers/ manufacturers of tobacco products	**1.03%**	0.13%	0.00%	0.11%	0.00%
Companies with 5% or more of revenues from tobacco production and/or distribution	**1.28%**	0.35%	0.00%	0.36%	0.00%
Coal involvement					
Coal Industry companies	0.11%	0.00%	0.00%	0.10%	0.00%
Companies with 30% or more of revenues from thermal coal mining	0.00%	0.00%	0.00%	0.00%	0.00%
Utilities with 30% or more of coal in power generation mix	1.98%	4.49%	0.00%	2.19%	0.00%
Companies owning coal reserves (exc. Iron and Steel Industry)	2.30%	2.56%	0.00%	1.92%	0.00%
Norm Violations					
Companies facing critical controversies in fundamental areas covered by the Global Compact or ineligible to be recognized as participants of the Global Compact	**13.62%**	5.46%	0.00%	7.52%	0.00%
Companies that only list non-voting stocks (from June 2019)	N.A.	N.A.	N.A.	N.A.	N.A.

EXHIBIT 5

Factor Exposures in CAPM and 7-Factor Model for Various Indexes, Developed Universe, 10 Years

Factor Exposures Metrics – Regressions Based Analyses Scientific Beta Developed Universe 10 years ended December 2018	CWI		MBMS HFI 6F EW		MBMS HFI 6F EW Sector Neutral	
	Standard	ESG option	Standard	ESG option	Standard	ESG option
CAPM Alpha	-	-0.10%	**3.40%**	**3.37%**	**2.84%**	**2.59%**
CAPM Beta	-	**1.01**	**0.84**	**0.85**	**0.87**	**0.88**
CAPM R Squared	-	99.92%	96.73%	97.00%	97.77%	97.74%
Seven-Factor Alpha	-	-0.18%	0.52%	0.41%	0.82%	0.43%
Market Beta	-	**1.01**	**0.85**	**0.86**	**0.88**	**0.88**
SMB* Beta	-	0.00	**0.15**	**0.15**	**0.14**	**0.14**
HML* Beta	-	**-0.02**	**0.07**	**0.07**	**0.08**	**0.08**
MOM* Beta	-	0.00	**0.08**	**0.08**	**0.08**	**0.08**
Low Vol* Beta	-	**-0.01**	**0.17**	**0.13**	**0.11**	**0.10**
High Prof* Beta	-	**0.02**	**0.14**	**0.21**	**0.11**	**0.14**
Low Inv* Beta	-	**-0.03**	0.05	**0.06**	0.02	0.00
Seven-Factor R Squared	-	99.93%	98.21%	98.30%	98.45%	98.44%
Factor Intensity	-	-0.03	0.67	0.70	0.53	0.55

EXHIBIT 6

Number of Constituents and Deconcentration of Various Indexes, Developed Universe, December 2018

Number of Constituents and Deconcentration Scientific Beta Developed Universe December 2018	CWI		MBMS HFI 6F EW		MBMS HFI 6F EW Sector Neutral	
	Standard	ESG option	Standard	ESG option	Standard	ESG option
Number of Constituents	1,467	1329	901	834	925	842
Effective Number of Constituents	276	232	502	455	389	373

As such, the ESG fiduciary option is particularly relevant to ethical and socially responsible investors

EXHIBIT 7

Performance, Risk-Adjusted Performance and Conditionality of Various Indexes, Developed Universe, 10 Years

Ten-year performance to end 2018 Scientific Beta Developed Universe	CWI		MBMS HFI 6F EW		MBMS HFI 6F EW Sector Neutral	
	Standard	ESG option	Standard	ESG option	Standard	ESG option
Annualized Returns	10.10%	10.07%	12.30%	12.43%	12.03%	11.82%
Annualized Volatility	14.34%	14.44%	12.42%	12.67%	12.84%	12.95%
Sharpe Ratio	0.68	0.67	0.96	0.95	0.91	0.88
Maximum Drawdown	26.51%	26.66%	22.84%	22.77%	22.66%	22.68%
Annualized Relative Returns	-	-0.03%	2.19%	2.32%	1.93%	1.72%
Annualized Tracking Error	-	0.48%	3.01%	2.81%	2.48%	2.43%
Information Ratio	-	-0.07	0.73	0.83	0.78	0.70
Historical Prob. of Outperformance (1Y)	-	41.93%	76.88%	80.20%	84.89%	82.89%
Historical Prob. of Outperformance (3Y)	-	42.21%	99.13%	98.96%	100.00%	100.00%
Historical Prob. of Outperformance (5Y)	-	38.12%	100.00%	100.00%	100.00%	100.00%
Bull-market Relative Return	-	0.50%	-3.68%	-2.53%	-2.44%	-2.34%
Bear-market Relative Return	-	-0.48%	7.27%	6.41%	5.61%	5.12%

Corporate governance

Given the separation of ownership and management, a central element of corporate governance is the protection of shareholders' rights. The G20/OECD Principles of Corporate Governance recognize voting rights as one of the basic shareholder rights. Consistent with this global norm, the ESG fiduciary option screens out companies that only issue non-voting shares to the public and thus deny investors the capacity to exercise oversight.

Controversial weapons

Controversial weapons are weapons that violate fundamental humanitarian principles due to their disproportionate or indiscriminate impact. As such, they are prohibited under international customary law and their use may be explicitly prohibited or regulated by international treaties. Investment in companies with involvement in some of these weapons is prohibited in certain jurisdictions and may expose the investor and its staff to legal risks and liability risk.

The ESG fiduciary option screens out companies with involvement in any one or several of 10 classes of inhumane weapons: anti-personnel landmines and cluster munitions; nuclear, bacteriological and chemical weapons; weapons using non-detectable fragments, incendiary weapons and blinding laser weapons; and depleted uranium weapons and white phosphorus munitions. This filter relies on data provided by Vigeo-Eiris.

Tobacco production and distribution

Tobacco consumption is now universally recognized for the major health risk it is and the significant economic toll it imposes on the affected individuals, their employers and governments. The 2003 World Health Organization Framework Convention on Tobacco Control does not ban tobacco but aims to reduce its prevalence. In support of this objective, the ESG fiduciary option excludes manufacturers of tobacco and tobacco products and companies that derive 5% or more of their revenues from the production or distribution of tobacco. This covers ownership of tobacco plantations, manufacture of tobacco products, sale of own products and wholesaling and retailing of tobacco products manufactured by other companies. This filter relies on data provided by Vigeo-Eiris.

Climate change

The 2015 Paris Agreement under the 1992 United Nations Framework Convention on Climate Change is a universal and legally binding agreement whereby 195 nations agree to work jointly to limit global temperature rise this century below 2 degrees Celsius. Continued reliance on coal is inconsistent with the objective of this global norm, which explains why the ESG fiduciary option screens out companies with significant coal involvement. The latter is defined by coal industry classification, ownership of reserves (except for Iron and Steel companies), 30% or more of revenues from thermal coal, and reliance on coal for 30% or more of the power generation capacity for Utilities. This filter relies on data provided by Institutional Shareholder Services.

Risks and Performances of ESG Multi-Smart-Factor Indexes

ESG performance

Exhibit 4 shows the weight of companies with controversial products/activities and conducts in the developed markets benchmark and in the standard and ESG option versions of our flagship index. By design, the exposure of the ESG fiduciary option indexes to companies targeted by the exclusionary screens is zero.

Analytics allowing for a deep dive into stranding risk show that the application of the coal-involvement filter reduces the potential greenhouse gas emissions associated with coal reserves by 95% relative to the benchmark, and tilts the fuel mix of power-generation companies significantly away from coal.

Financial Risks and Performance

The two sources of long-term benchmark-relative outperformance that the Scientific Beta multi-smart-factor index methodology exploits are the exposure to rewarded risk factors and the diversification of unrewarded idiosyncratic risk.

Exhibit 5 shows that ESG filtering does not reduce the potential for adding value with common factor tilts. Factor regressions also fail to uncover evidence of abnormal performance once factors beyond the broad market risk are recognized. In other words, the historical record does not support the idea that ESG filtering applied to the developed universe adds to or subtracts from the performance of derived indexes once loadings on consensus factors are accounted for.

Exhibit 6 illustrates that despite the reduction in the number of constituents linked to exclusions, ESG fiduciary option indexes remain significantly more deconcentrated than the benchmark, leaving good potential for adding value through diversification of idiosyncratic risk.

Finally, Exhibit 7 shows that the ESG fiduciary options of Scientific Beta's flagship indexes perform in line with their standard counterparts over the last 10 years. •

CONCLUSION

The ESG fiduciary option applicable across Scientific Beta's flagship offering allows investors to implement multi-smart-factor strategies while avoiding investment in companies that either fall short of global standards of responsible business conduct and corporate governance or have involvement in activities that conflict with global norms or their objectives.

The exclusionary approach followed by Scientific Beta for the incorporation of these global norms is consistent with

- A deontological approach of dissociation from companies involved in controversial products and conducts;
- A consequentialist approach aiming to incentivize the espect of global norms;
- A self-interested approach of avoidance of investments that may create reputational and liability risk for the investor or expose its portfolio to ESG risks with potential adverse material financial impacts.

The approach sends clear signals to issuers and is straightforward to explain to stakeholders, which provides protection against accusations of ESG washing.

The approach delivers indexes that have zero exposure to

- Companies that are identified as being involved in in humane weapons;
- Tobacco industry companies, tobacco product manufacturers and companies deriving significant revenues from tobacco production or distribution;
- Coal industry companies, companies with significant involvement in thermal coal mining or coal reserves
- Utilities with significant coal usage in power production.

The ESG Fiduciary Option also screens out companies that face critical controversies in respect of fundamental norms of responsible business conduct or oppose oversight by and accountability to public investors by denying them voting rights.

Over the last 10 years, the ESG fiduciary option has protected the sources of financial outperformance of the Scientific Beta multi-smart factor offering and indexes to which the option has been applied have performed in line with their unfiltered counterparts.

As such, the ESG fiduciary option is particularly relevant to ethical and socially responsible investors who wish to implement multi-factor investment strategies and to business-case multi-factor investors who wish to mitigate ESG risks as a precaution.