Scientific Beta

An EDHEC-Risk Institute Venture

AUTUMN 2018

RESEARCH INSIGHTS

EDHEC

EDHEC BUSINESS SCHOOL

An EDHEC publication in association with

INVESTMENT & PENSIONS EUROPE

IPE

Contents

IPE International Publishers Ltd
1 Kentish Buildings, 125 Borough High Street, London SE1 1NP, UK
Tel: +44(0)20 3465 9300, Fax: +44(0)20 7403 2788, Website: www.ipe.com, ISSN 1369-3727

Introduction

It is a great pleasure to introduce the latest Scientific Beta special issue of the Research Insights supplement to IPE.

We first show that achieving robust exposure to long-term rewarded factors, good diversification of unrewarded risks, and high levels of investability are key requirements for adding value with factor indices. It is clear that this added value is expressed over the long term, but that risk control options can increase the short-term consistency of the outperformance that investors expect.

In this short-term risk control context, we review the sector risk control option offered to investors by Scientific Beta that has been available on its platform since its launch in 2013. We conclude that the choice of using the sector risk control option is a trade-off between investors' aversion to short-term risks generated by sector risk and their willingness to harvest factor risk premia in the most efficient way, to achieve the highest risk-adjusted performance over the long run.

On the subject of allocation between factors, ERI Scientific Beta has undertaken extensive research to go beyond the usual approaches based on factor deconcentration or factor balance. In particular, we focus our research on the link between economic states and factor risk premia. We review some of the existing studies in this area from practitioners and then discuss conceptual considerations regarding the selection of relevant variables and propose a methodology for classifying macroeconomic regimes. We analyse the conditionality of factor premia to the macro regimes and give illustrative examples for implications for factor investors.

With more than $34bn in assets replicating our indices, we are now in a good position to observe instances of factor strategy implementation in institutional investors' allocations. As such, we felt that it was useful in this area to hear from one of our clients, OPTrust, with which we engage in intellectual exchanges that go well beyond a simple client/provider relationship. The portfolio construction team at OPTrust explains its approach to factor investing from a total portfolio construction perspective. They believe that their mission is best accomplished by building a portfolio with balanced exposures across different risk factors, including macro and style factors. Constructing the portfolio in this way has reduced their dependence on common risk drivers, such as equity risk, to earn the returns they need to keep their plan sustainable, at the lowest level of risk.

Finally, since allocating to factors implies that one knows how to identify them and how to measure a portfolio's exposures to them, we examine factor definitions used in analytic tools offered to investors and contrast them with the standard academic factors. We also outline why the methodologies used in popular tools pose a high risk of ending up with irrelevant factors. Most popular factor analysis tools used by investors deviate from the models used in research because they choose to use factor scores instead of betas. Although scores are easy to compute and present a point-in-time snapshot of portfolio characteristics, factor scores have serious shortcomings when it comes to factor exposure measurement. The consequence of this misalignment is that investors may end up with returns that fall short of their expectations.

We hope you will find the articles on smart beta in the supplement informative and relevant. We extend our warmest thanks to IPE for their partnership on the supplement.

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

Adding value with factor indices:

Sound design choices and explicit risk control options matter

Noël Amenc, Associate Dean for Business Development, EDHEC Business School, CEO, ERI Scientific Beta; **Patrick Bielstein**, Senior Quantitative Analyst, ERI Scientific Beta; **Felix Goltz**, Head of Applied Research, EDHEC-Risk Institute, Research Director, ERI Scientific Beta

We show that achieving robust exposure to long-term rewarded factors, good diversification of unrewarded risks, and high levels of investability are key requirements for adding value with factor indices.

Suitably designed smart factor indices address the shortcomings of cap-weighted indices (high concentration and poor exposure to risk factors).

In addition to factor risks, investors need to consider implicit risks, such as sector and market risk. We demonstrate how an investor can make explicit choices regarding these risks.

Multi-factor equity strategies have gained considerable traction with investors in recent years, and there is a multitude of choices when it comes to constructing or selecting factor-based equity strategies. However, simply tilting towards factors does not necessarily ensure sound investment outcomes. Instead, investors need to assess strategy design features carefully in order to understand the risk and performance properties that can be expected from such strategies. In this article, we address the issues arising in multi-factor strategy construction using the example of Scientific Beta indices. These indices are based on an investment philosophy that is motivated by a search for robustness at all stages of the index design process and is guided by the following three key principles:

- Offering exposure to long-term well-rewarded risk factors, whose existence and persistence have been documented by empirical studies and economic rationale;
- Ensuring a good reward for these factors through diversification of unrewarded (specific) risk, to increase long-term risk-adjusted performance while reducing short- and medium-term risk;
- Sound risk management by implementing risk allocation between smart factor indices, through explicit and transparent control over individual factor sleeves. This allocation allows investors to choose their factor exposures, but also – within the framework of dynamic allocation – to be able to satisfy particular absolute or relative risk objectives. Finally, the risk control options offered by Scientific Beta also make it possible to respond to important fiduciary choices for investors or their asset managers, such as whether or not to respect sector neutrality, country neutrality or use a market beta adjustment, which allows the market beta of the multi-factor strategy to be aligned with that of the market.

In this article, we first discuss how smart factor indices that address robustness, diversification and investability issues can be designed, and how such indices can be combined into multi-factor portfolios. Second, we turn to risk control options that allow sector and market exposure biases in multi-smart-factor indices to be addressed. Finally, we conclude on the consequences in terms of investors' positioning with respect to fiduciary choices and the corresponding expectations that they can have for their investment in a multi-smart-factor index.

Designing smart factor indices

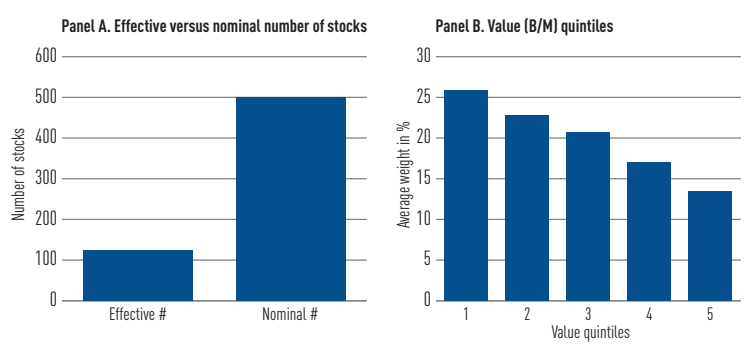
Ultimately, smart beta index design aims to remedy issues with cap-weighted indices, by drawing on well-documented sources of return and diversification. We first review the issues with cap-weighted indices and then outline key principles underlying smart beta index construction.

Smart beta indices versus cap-weighted indices

Indices that weight their constituents by their market capitalisation – cap-weighted (CW) indices for short – are still the most prevalent passive investment instruments and are widely used as 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 under-diversification means that unrewarded or stock idiosyncratic risks are not completely diversified away, leaving the investor exposed to such unwanted risks. Second, cap-weighted indices tend to have negative exposure to well-documented long-term rewarded risk factors. For example, due to the concentration in large-cap stocks, which also tend to be growth stocks (low book-to-market ratio), cap-weighted indices have a negative exposure to the size and value factors. Numerous academic studies have shown that small stocks outperform large stocks and that value stocks (high book-to-market ratio) outperform growth stocks in the long term.[1]

In figure 1, we show the effective and nominal number of stocks in the EDHEC-Risk US Long-Term Track Record (LTTR) cap-weighted index. A low effective number of stocks indicates high concentration.[2] The fact that the effective number of stocks is only about 100 while the nominal number of stocks is 500 shows that the cap-weighted index is heavily concentrated in relatively few stocks. Figure 1 also shows the weight allocation in the cap-weighted index for

1. Drawbacks of cap-weighted indices



This figure shows the effective and nominal number of stocks in the EDHEC-Risk US Long-Term Track Record (LTTR) cap-weighted index and the average weight allocation by value quintile between 31 December 1976 and 31 December 2016. The LTTR cap-weighted index consists of the 500 largest stocks by market capitalisation in the US. We compute the effective number of stocks as the sum of the squared weights of each stock in the index and average this figure over the sample period. We build book-to-market quintiles every quarter and show the average weight allocation over the sample period.

1 See footnote 3 for an overview of academic studies relating to risk factors.

2 The effective number of stocks in an equal-weighted index is identical to the nominal numbers. Thus holding 500 stocks with market cap weights is as concentrated as holding only about 100 stocks with equal weights.

each book-to-market quintile. It is apparent that large stocks and growth stocks dominate, which is expected to hinder long-term returns.

Smart factor indices ultimately address both shortcomings of cap-weighted indices, high concentration and exposure to the wrong factors. Designing smart factor indices thus requires employing suitable methods to capture factor premia and improve diversification.

Choice of factors

While we have seen that cap-weighted indices are poorly exposed to long-term rewarded factors, choosing a suitable set of rewarded factors raises important questions. In fact, only a rigorous factor selection procedure will lead to robust out-of-sample performance. The chosen factors should be supported by both theoretical and empirical academic evidence. We believe in established and well-documented factors over proprietary and over-engineered ones: size, value, momentum, low volatility, high profitability and low investment are the six factors on which we build our indices.[3]

There is strong empirical evidence that these factors deliver a premium over the cap-weighted market return in the long term. However, empirical evidence is only a necessary, and not a sufficient, condition for including a factor in our selection. As many researchers are looking for patterns in the same datasets on stock returns and statistical tests are usually designed with a level of significance of 5% (ie, the probability of wrongly finding a significant factor is 5%) when testing say 100 factors, five will be significant by chance. Indeed, Harvey, Liu and Zhu (2016) surveyed the academic literature and found 314 'significant' factors. The authors recommend using stricter levels of significance in the statistical tests and highlight the importance of having an economic rationale for factors. We show an overview of established economic rationales behind our chosen six factors in figure 2.

The risk-based explanations not only give confidence to the investor that the factors will persist in the future but also help alleviate factor crowding concerns, as some investors will be unwilling to take on these risks even if there is a long-term reward.

Robust factor definitions

Several factors have been well documented in the literature, as discussed above. An important question is how to implement such findings in practice, through an appropriate definition for each factor. A key requirement for benefiting from the substantial academic evidence on factors cited above is to use straightforward and established factor definitions that underlie this evidence. Using these standard factor definitions improves robustness and makes strategies easily tractable for investors. In contrast, constructing complex provider-specific factor definitions deconnects factor indices from the academic evidence. Such complex definitions increase data-mining risks and may lead to poor out-of-sample performance. We summarise the definitions used by Scientific Beta for the six factors in figure 3. Scientific Beta calculates scores yearly on the first Friday of June. The exception to the yearly rebalancing is the momentum factor, which is rebalanced twice a year (on the first Friday of June and December).

Some factor scores (value, profitability and investment) are based on accounting data. Accounting data can be difficult to compare across sectors (eg, book value for a bank has a very different meaning than book value for a manufacturing company), which would lead to a lack of relevance in the stock selection when comparing stocks across sectors with heterogeneous accounting properties. To avoid comparing apples with oranges – ie, to make sure that the factor-based stock selections reflect economic realities rather than sector-specific accounting discrepancies – Scientific Beta performs the stock filtering based on the factor score by mega-sector. Our mega-sectors are financials, technology firms, and others. This highly parsimonious approach allows stock diversity and factor intensity to be reconciled in each factor selection.

Applying such consensual factor definitions to select stocks for the relevant factor tilts is a first important step towards the design of smart factor indices. However, focusing only on stocks with the highest factor scores for a single factor ignores potential negative interaction effects with other factors. For example, a stock with a high book-to-market value might have a low momentum score. Thus, investors would benefit from additional controls in the stock selection mechanism to account for such interaction effects.

Controlling factor interactions

To address the issue of factor interactions, different alternatives exist. Many smart beta providers, being conscious of the factor interaction problem, compute a composite multi-factor score, which is then used for stock selection (referred to as the 'bottom-up' approach). Scientific Beta prefers to use the so-called 'top-down' approach, in which multi-factor indices are constructed from single-factor indices. Amenc et al (2017) show that while the 'bottom-up' approach leads to higher factor exposures than the 'top-down' approach, it also faces some major disadvantages, such as higher unrewarded risks caused by higher portfolio concentration. The authors document that the 'top-down' approach provides better performance per unit of factor exposure due to better diversification. They demonstrate an elegant solution to increase factor intensity in the 'top-down' approach by eliminating stocks with low multi-factor scores. Figure 4 shows interesting asymmetry between factor champions and factor losers. The absolute underperformance of a 'factor losers' portfolio is substantially larger than the outperformance of a 'factor champions' portfolio. This holds for two different ways of aggregating individual factor scores. Therefore, eliminating factor losers may be a more efficient way to increase factor intensity than focusing on factor champions.

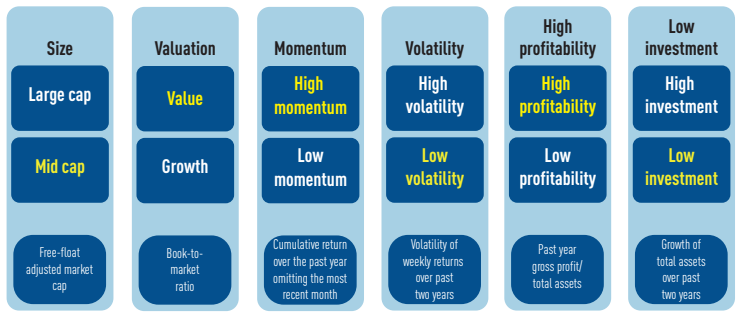
To put these findings into practice, Scientific Beta uses a factor intensity filter, which eliminates stocks with the lowest multi-factor scores. We calculate the multi-factor score based on the following factors: value, momentum, low volatility, high profitability and low investment. The size score is not included as our diversified indices already have a tilt towards small-cap stocks. While Scientific Beta offers a choice of two different specifications of the factor intensity filter, for the purposes of this article we will focus on presenting results for indices that use the high factor intensity (HFI) filter. This starts with

3 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.

2. Economic rationale behind selected factors

Factor	Risk-based explanation	Behavioural explanation
Size	Smaller stocks have lower liquidity, higher distress and downside risk	Limited investor attention to smaller cap stocks
Value	Value stocks find it harder to reverse their assets in bad economic times than growth stocks	Overreaction to bad news and extrapolation of the recent past leads to underpricing
Momentum	Investor is exposed to momentum crashes	Investor overconfidence and self-attribution bias lead to higher returns in the short term
Low volatility	Liquidity-constrained investors have to sell leveraged positions in low-risk assets in bad times when liquidity constraints become binding	Disagreement among investors about high-risk stocks leads to overpricing due to short sale constraints
High profitability	Firms facing high cost of capital will invest only in the most profitable projects	Investors do not discern high and low profitability in growth firms
Low investment	Low investment indicates a firm's higher cost of capital	Investors underprice low investment firms due to expectation errors

3. Scientific Beta's scoring criteria

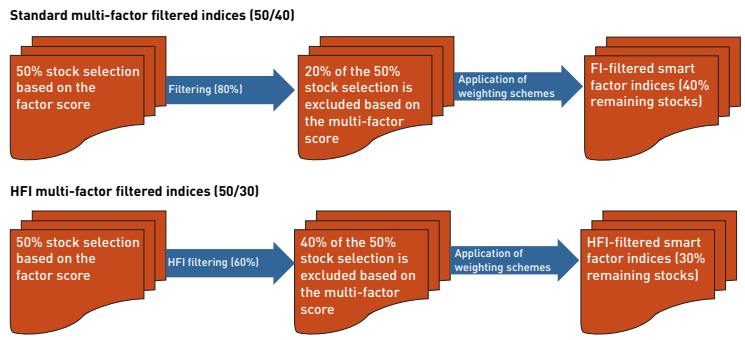


4. Factor champions vs factor losers

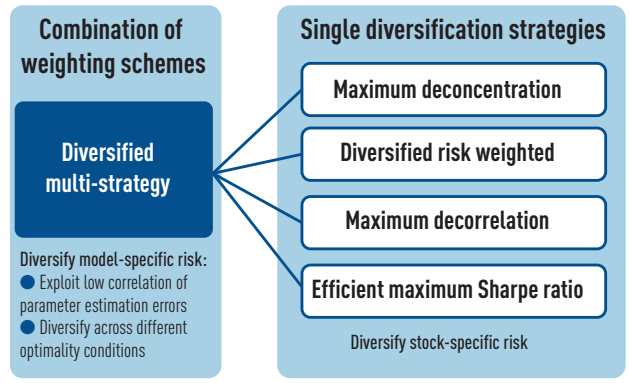
EDHEC-Risk US LTTR	Geometric mean		Arithmetic mean	
31 December 1976–31 December 2016	Champions	Losers	Champions	Losers
	5% stock selection			
Annualised relative return	4.02%	–8.66%	2.87%	–6.79%
Factor intensity	1.06	–1.97	0.97	–1.56

This figure shows annualised relative returns and factor intensity for factor champion and factor loser portfolios. Relative returns are excess returns over the cap-weighted index. Factor intensity is the sum of factor coefficients excluding the market factor from regressing excess portfolio returns (champion and losers portfolios, excess with respect to the risk-free rate) on a seven-factor model (factors include market, size, value, momentum, low volatility, high profitability, low investment; all non-market factors are dollar-neutral long/short portfolios). We build factor champion portfolios by selecting the stocks with the highest multi-factor score. The threshold is the 95th percentile of the multi-factor score distribution. We calculate multi-factor scores by taking either the geometric average or the arithmetic average of six individual factor scores (size, value, momentum, low volatility, high profitability, low investment). Factor scores are normalised rank scores. We use daily total returns from 31 December 1976 to 31 December 2016. The data source is the EDHEC-Risk US LTTR database. The cap-weighted index is based on the 500 largest stocks by market capitalisation in the US. We use the three-month US Treasury bill rate as the risk-free return.

5. Standard vs high factor intensity filtered smart factor indices



6. Diversified multi-strategy weighting scheme



stocks that are part of the factor-based selection (which contains 50% of stocks in the entire universe) and excludes stocks with the lowest multi-factor score, leaving 30% of stocks compared to the starting investment universe. The other specification of the factor intensity filter is the standard factor intensity filter, which filters out a smaller number of stocks, leaving 40% of stocks compared to the starting investment universe at the end of the process.

The key advantage of the factor intensity filter is that it allows us to take factor interactions into account and achieve stronger factor intensity in a multi-factor setting through ERI Scientific Beta's consistent 'top-down' framework. The flexibility and transparency of 'top-down' approaches is retained and so is the efficient premium capture of the smart factor indices. Figure 5 illustrates the filters by comparing both the standard and HFI-filtered smart factor indices. The HFI version of this multi-factor intensity filter achieves much higher intensity and corresponds to the choice that is favoured by investors who wish to have a substantial factor distance with respect to the cap-weighted index, and consequently higher tracking error than that displayed by the standard multi-beta multi-strategy (MBMS) indices.

Diversifying specific risks

A crucial question when constructing factor indices is not only how to gain exposure to rewarded risk factors, but also how to limit the exposure to unrewarded risks. Scientific Beta addresses this question in the Smart Beta 2.0 approach for constructing smart factor indices (Amenc and Goltz [2013]). This approach breaks down the index construction into two distinct steps: first, filter the investment universe according to the desired risk factor (eg, select the top 50% stocks based on their book-to-market value), and apply relevant filters to control for cross-factor interaction. Second, diversify away unrewarded (idiosyncratic) risks through a smart weighting scheme (eg, through equally weighting each stock). A key advantage of this approach is that it not only considers the question of factor exposure, but also that of diversifying stock-specific risk through a suitable weighting scheme. Moreover, the Smart Beta 2.0 approach allows for the introduction of additional risk options in a straightforward way. We will discuss the importance of risk control options in the second part of this article.

It is important to recall why, after filtering the stock universe according to the desired factor tilt and eliminating factor losers to increase factor intensity, the question of how to diversify idiosyncratic stock risk is crucial. In fact, the starting point of designing a smart beta strategy was to address the shortcomings of cap-weighted indices. Selecting stocks based on factor characteristics deals with one of the shortcomings. However, if factor-tilted indices were constructed with a high level of concentration, investors would be exposed to stock-specific risks, and suffer the same concentration problem as that which is inherent in cap-weighted indices. To address the shortcomings of cap-weighted indices fully, one needs to improve both factor exposures and diversification.

In order to improve diversification, we need to choose a diversifying weighting scheme when designing sound factor indices. Several suitable weighting schemes exist that allow stock-specific risk to be diversified, including the maximum deconcentration, diversified risk weighted, maximum decorrelation and maximum Sharpe ratio approaches. These weighting schemes are based on different definitions of diversification, such as balancing dollar weights (maximum deconcentration) or exploiting the risk reduction benefits of low correlations across stocks (maximum decorrelation). While an investor could in principle select one of these weighting schemes, selecting a single weighting scheme would leave one exposed to model risk.

The risk of choosing a particular weighting scheme is not rewarded and can contribute to a lack of robustness of smart beta strategies (Amenc et al [2015]). According to Modern Portfolio Theory and in the absence of measurement errors, the maximum Sharpe ratio (MSR) portfolio is the most efficient weighting scheme. In practice, however, inputs for the MSR portfolio are measured with error, which can lead to poor ex-post portfolio performance. The MSR portfolio uses expected stock returns and the corresponding covariance matrix as inputs. It is especially difficult to estimate stock returns reliably out-of-sample (Merton [1980]). The different weighting schemes discussed above avoid direct estimation of expected returns, and instead use risk parameters, which can be estimated more reliably. However, these portfolios will only coincide with the theoretically optimal MSR portfolio under a particular set of assumptions. For example, the maximum deconcentration scheme is optimal if all stocks have the same expected return and the same risk parameters. While this assumption is unrealistic, the strategy does not suffer from measurement error in the inputs. Thus, the investor faces a trade-off between optimality risk and parameter estimation risk. Since each weighting scheme is different in terms of parameter estimation risk and optimality risk, investors can improve diversification by combining several weighting schemes.

Scientific Beta's approach is to combine four different weighting schemes in order to diversify the optimality and parameter estimation risks. The diversified multi-strategy weighting scheme equally weights the following strategies: efficient maximum Sharpe ratio, maximum deconcentration, maximum decorrelation and diversified risk-weighted (see figure 6). Diversifying across different models makes intuitive sense: just as an investor would typically not want to depend on a single manager to represent a given investment style, it is also appropriate to avoid depending on a single weighting scheme to capture a given factor. Diversifying model risk also adds a second layer of diversification to the first layer, which is the diversification of stock-specific risk, which each single weighting scheme achieves.

Figure 7 provides evidence of the benefits of Scientific Beta's weighting scheme diversification approach and of the usefulness of the HFI filter presented above.

7. Performance of Scientific Beta HFI diversified multi-strategy smart factor indices vs corresponding cap-weighted factor indices

EDHEC-RIsk US LTTR 31 Dec 1976–31 Dec 2016	Broad CW	Average of six factor-tilted CW indices	Average of six factor-tilted score-weighted indices	Average of six HFI diversified multi-strategy (four-strategy) indices
Annualised returns	10.86%	11.74%	11.87%	13.89%
Annualised volatility	17.07%	16.74%	16.69%	14.67%
Sharpe ratio	0.35	0.41	0.42	0.62
Annualised relative returns	–	0.88%	1.01%	3.03%
Annualised tracking error	–	4.38%	4.65%	5.80%
Information ratio	–	0.20	0.22	0.53
Idiosyncratic risk-adjusted return	–	0.10	0.12	0.43
Change in specific volatility	–	–0.54%	–0.65%	–2.66%

Daily total returns from 31 December 1976 to 31 December 2016 are used for the EDHEC Risk US LTTR universe. The six factor-tilted cap-weighted indices are SciBeta Long-Term United States Mid Cap Cap-Weighted, SciBeta Long-Term United States Value Cap-Weighted, SciBeta Long-Term United States High Momentum Cap-Weighted, SciBeta Long-Term United States Low Vol Cap-Weighted, SciBeta Long-Term United States High Profitability Cap-Weighted and SciBeta Long-Term United States Low Investment Cap-Weighted. The six HFI diversified multi-strategy indices are SciBeta Long-Term United States High-Factor-Intensity Mid Cap Diversified Multi-Strategy (4-S), SciBeta Long-Term United States High-Factor-Intensity Value Diversified Multi-Strategy (4-S), SciBeta Long-Term United States High-Factor-Intensity High Momentum Diversified Multi-Strategy (4-S), SciBeta Long-Term United States High-Factor-Intensity Low Vol Diversified Multi-Strategy (4-S), SciBeta Long-Term United States High-Factor-Intensity High Profitability Diversified Multi-Strategy (4-S) and SciBeta Long-Term United States High-Factor-Intensity Low Investment Diversified Multi-Strategy (4-S).

The average outperformance of the Scientific Beta HFI diversified multi-strategy smart factor indices versus the corresponding cap-weighted factor indices (ie, the factor-based stock selection but weighting the stocks according to their market capitalisation) and score-weighted factor indices (ie, the same factor-based stock selection but weighting stocks by their factor score) exceeds 2% per annum. We see significant improvements also in Sharpe ratios. The HFI diversified multi-strategy indices have, on average, a 50% higher Sharpe ratio compared to their cap-weighted counterparts. These results provide strong evidence of the benefits of smart factor indices over more concentrated factor indices, such as the corresponding cap-weighted and score-weighted factor indices.

It is clear from these results that diversification not only reduces specific volatility but also improves long-term risk-adjusted performance in comparison with traditional cap-weighted or non-diversified factor indices. Therefore, diversification of specific and unrewarded risks needs to be considered a core part of the design of factor indices.

Combining factor tilts

Having thoroughly analysed single-factor indices, we now turn to multi-factor allocations. It is intuitive that combining single-factor indices should improve risk-adjusted portfolio performance as different factors perform well in different periods. Several researchers document that factor portfolio performance varies over time (Harvey [1989], Asness [1992], Cohen, Polk and Vuolteenaho [2003]). If these return series are not perfectly positively correlated then an investor should benefit from combining different factor portfolios. In figure 8, we show how six long/short factors perform over time.

To illustrate the potential benefits of a multi-factor portfolio we have computed the pairwise correlations between relative returns (relative to the cap-weighted market return) of different factor indices (see figure 9). Note that the correlations are low overall and even negative between some factor indices. Besides the diversification benefits, this also points to potentially lower tracking error relative to the cap-weighted benchmark of multi-factor indices. These findings are consistent with other studies. For example, Ilmanen and Kizer (2012) find that factor diversification is more effective than asset class diversification and that the benefits of factor diversification are still substantial even for long-only investors.

Liquidity and investability

Investability is a natural challenge for smart beta indices. In fact, by deviating from market capitalisation weights and by periodically adjusting strategy weights, smart beta indices incur potential investability hurdles that cap-weighted indices easily avoid. Investors thus need to consider carefully whether the benefits of smart beta indices documented on paper also carry through in practice. In this section, we will discuss how suitably designed implementation rules can be used to construct highly investable factor indices.

Investability needs to be addressed systematically, at three different levels of smart beta strategies. First, the liquidity of the universe needs to be ensured. Indeed, by constructing strategies from a carefully designed universe of sufficiently liquid stocks, smart beta strategies make a first important step towards smooth investability. Second, liquidity needs to be ensured at the strategy level. Index rules need to explicitly address how the strategy will avoid problematic weights or weight changes relative to the available liquidity in a given stock. Indeed, even within a liquid universe, rebalances need to consider a set of limits with respect to available volume and market capitalisation for example. Third, investors expect factor indices to maintain a reasonably low level of turnover. Mechanisms to control turnover are necessary in factor index design so as to improve investability. It should be noted that all results on index performance presented in this article use Scientific Beta indices that do integrate suitable implementation rules for each of these three dimensions and thus achieve high levels of investability.

While a detailed description of the implementation rules is beyond the scope of this article, we will discuss selected aspects below. For a more detailed discussion of implementation rules, we refer the reader to Amenc, Goltz and Sivasubramanian (2017).

In order to achieve a highly-liquid investment universe, Scientific Beta indices apply two fundamental principles/objectives that guide the construction of a universe that is appropriate for investment in non-cap-weighted universes:

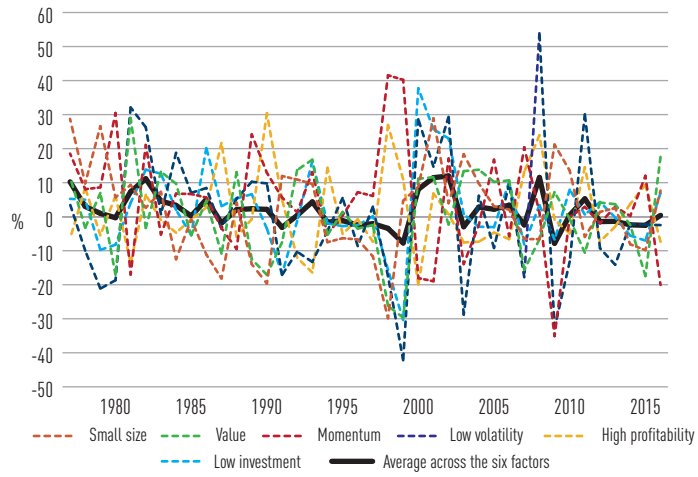
- Respecting geographic basic blocks. Both the factor selections and the application of the weighting schemes are carried out within these blocks. For example, the developed market universe consists of blocks representing fairly homogeneous regions, such as Japan, the US and the euro-zone. This regionalisation of the index construction avoids microeconomic factor choices resulting in macroeconomic imbalances. Ultimately, the index construction respects broad geographic neutrality with respect to cap-weighted indices.
- A strong liquidity requirement. Given the distance from cap-weighting that results from alternative weighting schemes and factor selection, it is important to ensure that the universe of investable stocks is highly liquid and guarantees sufficient investment capacity.

In practice, these principles lead to universes for developed markets and emerging markets that contain 1,470 and 670 stocks respectively. To strengthen the liquidity of stocks retained in each geographic block, a liquidity screen is applied, which reflects strong requirements in terms of distinct dimensions of liquidity (such as absolute and relative volume indicators and trading ratio requirements). Scientific Beta also accounts for foreign room available to investors when a security is subject to a foreign ownership limit. Such mechanisms have a significant positive impact on the investability of the universe.

In order to achieve investability at the level of the strategy index that is constructed from the liquid universe, several rules need to be considered. For example, Scientific Beta employs capping rules, which aim to strengthen the investability of the indices in reference to capacity/liquidity expressed in relation to the cap-weighting of the stocks. These liquidity rules facilitate the capacity of the smart factor indices and avoid creating exposure to stocks with low levels of liquidity. Additional rules explicitly consider the available trading volume and allow the indices to respect bounds on the average days-to-trade that result from weight changes at the index rebalancing date.

8. Time-varying factor premiums

Annual return spread of long-short CW factors



This figure shows the annual returns for selected factors over time. The size factor is long the smallest 30% stocks ranked by market capitalisation and short the largest 30% stocks ranked by market capitalisation. The value factor is long the highest 30% stocks ranked by book-to-market ratio and short the lowest 30% stocks ranked by book-to-market ratio. The momentum factor is long the highest 30% stocks ranked by the past 12 month return omitting the most recent month and short the lowest 30% stocks ranked by the past 12 month return omitting the most recent month. The low volatility factor is long the lowest 30% stocks ranked by their standard deviation of returns over the preceding two years and short the highest 30% stocks ranked by their standard deviation of returns over the preceding two years. The high profitability factor is long the highest 30% stocks ranked by their gross profits over total assets ratio and short the lowest 30% stocks ranked by their gross profits over total assets ratio. The low investment factor is long the lowest 30% stocks ranked by their past two-year asset growth and short the highest 30% stocks ranked by their past two-year asset growth. All factors weight stocks by their market capitalisation. We also show the arithmetic average return across the six factors. The sample period starts on 31 December 1976 and ends on 31 December 2016. The data source is the EDHEC-Risk US LTTR database.

9. Correlation between relative returns of factor indices

	Size	Value	Momentum	Low volatility	High profitability	Low investment
Size	1.00					
Value	0.20	1.00				
Momentum	0.02	−0.36	1.00			
Low volatility	−0.24	0.36	−0.13	1.00		
High profitability	−0.25	−0.80	0.27	−0.16	1.00	
Low investment	−0.03	0.43	−0.07	0.70	−0.19	1.00

This figure shows correlations between relative returns of (long-only) factor indices. Relative returns are returns in excess of the cap-weighted market return. The size index selects the smallest 50% stocks ranked by their market capitalisation. The value index selects the highest 50% stocks ranked by their book-to-market value. The low volatility index selects the lowest 50% stocks ranked by their standard deviation of returns over the preceding two years. The high profitability index selects the highest 50% stocks ranked by their gross profitability. The low investment index selects the lowest 50% stocks ranked by their two-year asset growth. Correlations are based on daily total returns from 31 December 1976 to 31 December 2016. The data source is the EDHEC-Risk US LTTR database. The cap-weighted index is based on the 500 largest stocks by market capitalisation in the US.

Finally, turnover in the indices can be addressed with suitably designed control mechanisms. Among these mechanisms, it is straightforward to limit the rebalancing resulting from marginal changes in stock-level factor exposures. Scientific Beta uses buffer rules to reduce fluctuation in the stock selection due to marginal shifts in the ranking of stocks. In addition, Scientific Beta uses an optimal turnover control approach to limit index turnover. This approach is an implementation of optimal control strategies that have been developed to reduce transaction costs in dynamic portfolio strategies (see Martellini and Priaulet [2002]). At each quarterly rebalancing date, new weights are effectively implemented only if weight changes surpass a specified threshold. In addition to facilitating investability, this approach provides the benefit of making portfolio weights less sensitive to noise and thus more robust. In fact, small changes in strategy weights, which may be due to noise, will not be implemented.

Given their careful integration of implementation rules, Scientific Beta indices offer high levels of investability. Figure 10 displays investability indicators for the HFI Multi-Beta Multi-Strategy (MBMS) 6-Factor 4-Strategy index in comparison to the cap-weighted benchmark portfolio. The strong investability of the multi-factor index is directly apparent from these results. In fact, the index displays a reasonable annual turnover figure of approximately 35% that leads to negligible transaction costs (2 basis points) compared to the historical outperformance. The effective days-to-trade for the MBMS index is only 0.14, reflecting low hurdles to replication of such an index in practice.

Risk control adjustments

As shown in the previous section, investors benefit from investing in priced risk factors and improved diversification in the long-term. Despite these long-term benefits, factor-based indices also carry a number of implicit risks that could significantly influence short-term performance. These implicit risks need to be well documented so that asset owners can make an informed decision regarding the management of these risks. In this section, we highlight three implicit risks of smart beta indices and we discuss the advantages and disadvantages of controlling these risks.

Sector risk

As explained above, Scientific Beta performs the stock selection for its indices within mega-sectors as accounting figures can have vastly different meanings across sectors. However, even with this adjustment, the sector allocation of smart beta indices can differ substantially from the sector allocation of the cap-weighted market portfolio due to the stock-filtering process and weighting scheme. This increases the tracking error of a smart beta index and can materially affect its short-term performance. As described in Amenc and Goltz (2013), Scientific Beta offers sector-neutral versions of its indices to address sector allocation mismatches.[4] The procedure is as follows: first, the regional stock universe (for example, the 500 largest stocks by market capitalisation in the US) is divided into 10 sectors using the Thomson-Reuters Business Classification system. Then we calculate the factor scores within each sector (instead of on the whole investment universe) so that each sector will have high and low-scoring stocks. Finally, we combine the top scoring stocks within each sector into one pool for the given regional stock universe, thereby preserving its original sector allocation.

A sector-neutral factor index will have a lower tracking error and a reduced risk of short-term underperformance with respect to the cap-weighted benchmark. Scientific Beta has conducted empirical analyses that show that this comes at the cost of higher volatility and lower factor intensity (Aguet et al [2018]). These findings enable the investor to make an informed decision on sector neutrality.

Country risk

Country risk arises when the country allocation within an index differs from the country allocation of the cap-weighted benchmark portfolio. This is most pertinent when investing in a world index. The deviations from the country weights in the benchmark portfolio can be substantial and there is no evidence that taking on country risks is rewarded in the long term. Thus, Scientific Beta believes that it should be up to the investor (and not the index provider) to make an explicit decision on whether to take on country risk or not.

In line with these arguments, Scientific Beta builds regional indices by respecting the relative weight based on the market capitalisation of each region. Academic studies show that factor investing works best within economically integrated regions (Fama and French [2012]), which is the guideline for Scientific Beta. Within regions, Scientific Beta offers the option of country neutrality to mitigate country risk. The approach is similar to the sector-neutral approach in that the factor scores for each stock are determined for each country in the region. Then the top scoring stocks for each country are pooled to arrive at a country-neutral stock selection for the respective region.

Market beta adjustment

Most multi-factor smart beta providers focus on two areas: improving the performance associated with factor exposures and increasing the exposure to non-market factors in a multi-factor portfolio. Surprisingly little attention has been paid to the measurement and control of market beta in a multi-factor index, even though the market factor is the largest driver of performance and risk in a multi-factor portfolio. The market beta of a smart beta strategy is the result of several index construction choices but, in general, there is no explicit management of market beta and often it is lower than one as some factors and weighting schemes have a bias towards lower market beta stocks. This in turn can significantly affect performance and risk metrics of smart beta indices. Research by Scientific Beta shows that the market factor contributes more to the overall portfolio performance than the other factors combined (see figure 11). The cost of under-exposure to the market is over 1% per year in our US sample over the last 40 years. It can also negatively impact conditional portfolio performance during, for example, long bull markets

10. Liquidity and investability indicators of the flagship multi-beta multi-strategy (MBMS) index

SciBeta US 30 June 2008–30 June 2018	Cap-weighted benchmark	HFI Multi-Beta Multi-Strategy 6F 4S EW
Annualised turnover	3.76%	35.13%
Average capacity ($m)	108,512	34,753
Latest capacity ($m)	189,417	45,489
Average transaction costs	<0.01%	0.02%
Effective days-to-trade	0.01	0.14
Maximum days-to-trade	0.24	1.17

This figure compares the Scientific Beta HFI Multi-Beta Multi-Strategy 6F 4S EW index to the cap-weighted market portfolio in terms of liquidity and investability. The rows show different liquidity and investability indicators. Annualised turnover is computed as the sum of absolute deviations of individual weights between the end of a quarter and the beginning of the following quarter. The resulting two-way quarterly turnover is then annualised and divided by two to arrive at the one-way turnover. Capacity is the sum of each stock's weight in the portfolio times its free-float adjusted market capitalisation. The latest capacity is taken from 30 June 2018. We estimate transaction costs as the product of average spread (7bps, which is calculated based on closing quoted spread proposed in Chung and Zhang [2014]) for the 500 stocks in US during the period 2004 to 2014 and the average one-way turnover. To compute maximum days-to-trade, we first calculate days-to-trade for the last quarter in the sample as the free-float market capitalisation of the cap-weighted benchmark portfolio times the assumed investment amount of $3bn divided by the market cap of the global cap-weighted index ($34,777bn) times the weight of the stock in the portfolio divided by the product of average daily trading volume over the preceding quarter and 10%. Then we obtain the maximum days-to-trade as the 95th percentile of the days-to-trade distribution. For the effective days-to-trade, we first compute days-to-trade for each quarter according to the description above but using the absolute change in weights (compared to the previous quarter). Then we calculate the 95th percentile of the days-to-trade for each quarter. Finally, we average this figure over all quarters in the sample period. The sample period is 30 June 2008 to 30 June 2018 based on the Scientific Beta US database. Besides the cap-weighted benchmark portfolio, we include the HFI Multi-Beta Multi-Strategy 6F 4S EW index which combines six factor tilts (size, value, momentum, low volatility, high profitability and low investment, equally weighted) and four weighting schemes (efficient maximum Sharpe ratio, maximum deconcentration, maximum decorrelation and diversified risk-weighted). In addition, it applies the high factor intensity filter for the stock selection.

11. The importance of risk management – market risk

EDHEC-Risk US Long-Term HFI Multi-Beta Multi-Strategy 6-Factor EW index					
Factor exposure		**Performance attribution**		**Volatility attribution**	
Annualised unexplained	0.19%	Annualised unexplained	0.78%	Idiosyncratic component	0.66%
Market beta	**0.84**	**Market factor**	**4.80%**	**Market factor**	**12.67%**
SMB beta	**0.11**	SMB factor	1.01%	SMB factor	0.13%
HML beta	**0.14**	HML factor	0.19%	HML factor	0.15%
MOM beta	**0.06**	MOM factor	0.17%	MOM factor	0.05%
Low volatility beta	**0.12**	Low volatility factor	1.26%	Low volatility factor	0.26%
High profitability beta	**0.10**	High profitability factor	0.13%	High profitability factor	0.04%
Low investment beta	**0.07**	Low investment factor	0.35%	Low investment factor	0.01%
R-squared	95%			Interaction component	0.21%
Factor intensity	0.60				

The universe is the EDHEC-Risk US Long-Term Track Records. The time period of analysis is from 31 December 1976 to 31 December 2016 (40 years). The analysis is based on weekly total returns in US dollars. All statistics are annualised. The yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. The market factor is the excess return series of the cap-weighted index over the risk-free rate. The other six factors are market-neutral equal-weighted factors obtained from Scientific Beta. Coefficients significant at 5% p-value are highlighted in bold

4 For an in-depth discussion of sector risk, please see the article Managing sector risk in factor investing in this supplement (page 10).

Live is Better

Since 2013, with the Smart Beta 2.0 framework, EDHEC-Risk Institute has created Scientific Beta multi-smart-factor indices that are well diversified and exposed to rewarded factors. These indices have a robust live track record with annualised outperformance of 1.60% and an improvement in Sharpe Ratio of 47.50% compared to their cap-weighted benchmark.[1]

We believe that the academic consensus and concern for robustness that underlie the design of our smart beta indices are always demonstrated, not only in our long-term track records, but also in our live performances.

For more information, please visit www.scientificbeta.com
or contact Mélanie Ruiz on +33 493 187 851 or by e-mail to melanie.ruiz@scientificbeta.com

www.scientificbeta.com

1 - The average live outperformance and improvement in Sharpe Ratio across all Scientific Beta developed regions of Scientific Beta Multi-Beta Multi-Strategy (Equal Weight and Equal Risk Contribution) indices is 1.65% and 1.56% for the outperformance and 49.29% and 45.72% for the improvement in Sharpe Ratio. This live analysis is based on daily total returns in the period from December 20, 2013 (live date) to September 30, 2018 for all diversified multi-strategy indices that have more than 3 years of track record for all available developed world regions – USA, Eurozone, UK, Developed Europe, Developed Europe ex UK, Japan, Developed Asia Pacific ex Japan, Developed ex UK, Developed ex USA and Developed. The benchmark used is a cap-weighted portfolio of all stocks in the respective Scientific Beta universes.

when indices with market betas below one tend to underperform the cap-weighted market portfolio.

It is important to note that having a defensive index also means that the volatility is lower. Given this trade-off between risk and return, Scientific Beta believes that the investor should make an explicit choice regarding the level of market beta exposure. It is not up to the index provider to make a decision as important as the market exposure implicitly for the investor. Therefore, Scientific Beta offers investors the option to adjust the index market beta to one, depending on their preferences. We will describe the necessary steps for this adjustment. First, we need to forecast the index market beta precisely. Scientific Beta has implemented the approach developed in Amenc, Goltz and Lodh (2018). In general, the index's market beta forecast could be less than or greater than one, which in turn determines whether the index needs to be levered up or down to achieve a portfolio market beta of one. In Scientific Beta's applications, however, multi-factor indices always have a market beta less than one, so we will focus on that case here. To lever up the portfolio, we borrow cash at the overnight rate and invest the proceeds in the multi-factor index subject to the following constraints:

- The ex-ante market beta of the portfolio is equal to one;
- The portfolio is fully invested;
- The limit for borrowing cash is 30% of the portfolio value.

Please refer to the box below for the corresponding formulas. Note that instead of borrowing cash, it is also possible to lever up the index by using futures on the cap-weighted benchmark portfolio as an overlay. Scientific Beta offers indices that represent both market beta adjustment (MBA) options. Figure 12 allows the application of these two options to be compared for US and developed universes over the last 10 years. It is clear that the leverage option, when it is possible, allows better excess returns and better factor intensity to be obtained, but the implementation of an MBA with a CW overlay is often favoured by investors who do not wish to take counterparty risk or cannot borrow cash. The CW overlay option leads to better relative risk management expressed as tracking error or maximum relative drawdown.

Figures 13a and 13b show performance and risk measures for various Scientific Beta multi-beta multi-strategy indices using different risk-control options respectively for the US Long-Term Track Records (LTTR), which allows the long-term robustness of the strategies to be estimated, and the developed universe, which provides a view of the consistency of this performance across regions. First, we note that all smart beta indices significantly outperform the cap-weighted benchmark on a risk-adjusted basis (the average increase in the Sharpe ratio is 70% across both investment universes). Comparing the sector-neutral indices with their non-sector-neutral counterparts, we observe that the sector-neutral versions have a lower tracking error and a lower maximum relative drawdown, but this comes at the cost of a somewhat lower Sharpe ratio and lower factor intensity.

Portfolio statistics are markedly different for the indices with market beta adjustment. They show higher average returns and higher volatility leaving the Sharpe ratio about the same. However, they improve the relative performance and risk in both dimensions as they have higher relative returns and lower tracking error so that the information ratio is more than doubled compared to their non-market-beta-adjusted counterparts. We note significant improvements with respect to the maximum relative drawdown and conditional relative returns in bull and bear markets, ie, outperformance is less concentrated in bear markets and more evenly spread between these two market conditions.

The Multi-Beta Multi-Strategy 6 Factor HFI EW index is well suited for investors who are comfortable with taking the implicit risks described in this section. Depending on the investor's risk preferences, he or she can choose from various risk control options such as sector-neutrality, country-neutrality and a market beta adjustment. One observation that may be interesting in response to the doubts expressed in recent years on the usefulness of factor investing, notably in a systematic and passive way, is that the application of the sector-neutrality option, or even better, the sector-neutrality and market beta adjustment options, has provided outperformance every year for the last 10 years compared to the reference cap-weighted index. Figure 14 details the annual excess returns for both the US and developed markets for the Scientific Beta HFI Multi-Beta Multi-Strategy 6F 4S EW indices compared to the sector-neutral and sector-neutral plus MBA option versions.

Overall, this section shows that implicit risks in smart beta indices have a major impact on risk and performance. However, most index providers rarely report these risks, let alone offer risk control options to investors. Effectively, these index providers make implicit choices for the asset owners even though the fiduciary duty does not lie with them. There is no single best solution regarding implicit risks, but rather a best solution that allows asset owners to carry out their fiduciary duty in the most efficient way. Smart beta index providers should devote more attention to fully disclosing hidden and implicit

Market beta adjustment

We start by writing out the formula for the portfolio market beta, which we set to one:

$$\beta_{Lev}^{Mkt} = W_{Index} \cdot \beta_{Index}^{Mkt} + W_{Cash} \cdot \beta_{Cash}^{Mkt} = 1$$

$$W_{Index} + W_{Cash} = 1$$

Cash has a market beta of zero by definition. This lets us solve the first equation for the weight of the index:

$$W_{Index} = \frac{1}{\beta_{Index}^{Mkt}}$$

Next, we apply the constraint on borrowing:

$$W_{Index} = \max\left(W_{Index}, 1.30\right)$$

Finally we solve for the weight of cash:

$$W_{Cash} = 1 - W_{Index}$$

12. Performance and risk measures of MBMS indices with market beta adjustment options

30 June 2008–30 June 2018	US universe			Developed universe		
	Cap-weighted benchmark	HFI MBMS 6F 4S EW MBA (leverage)	HFI MBMS 6F 4S EW MBA (overlay)	Cap-weighted benchmark	HFI MBMS 6F 4S EW MBA (leverage)	HFI MBMS 6F 4S EW MBA (overlay)
Annualised average return	9.87%	13.61%	13.16%	6.62%	11.34%	10.70%
Annualised volatility	20.04%	20.68%	20.53%	16.94%	17.21%	17.13%
Sharpe ratio	0.48	0.62	0.62	0.37	0.64	0.60
P-value	–	1.90%	1.26%	–	0.02%	0.02%
Maximum drawdown	47.04%	47.74%	47.58%	49.94%	58.69%	48.83%
Relative return	–	3.40%	2.99%	–	4.42%	3.82%
Tracking error	–	3.87%	3.35%	–	2.73%	2.35%
95% tracking error	–	5.86%	5.03%	–	3.92%	3.35%
Information ratio	–	0.88	0.89	–	0.43	0.38
Maximum relative drawdown	–	8.10%	6.99%	–	5.69%	4.92%
Bull relative return	–	3.25%	2.86%	–	4.30%	3.69%
Bear relative return	–	3.97%	3.49%	–	4.55%	3.99%
Factor intensity	–	0.50	0.43	–	0.37	0.32

This figure shows Scientific Beta MBMS MBA indices with two different market beta adjustment methods (leverage and overlay) for the US and developed markets and the corresponding cap-weighted benchmark portfolios. The rows show different portfolio metrics. Annualised average return is the annualised geometric average return. Annualised volatility is the annualised standard deviation of portfolio returns. The Sharpe ratio is computed by dividing the annualised excess portfolio return (in excess of the risk-free rate) by the standard deviation of the excess portfolio return. The maximum drawdown is the highest loss from peak to trough in the observation period. Relative return is the geometric average excess portfolio return (in excess of the cap-weighted benchmark return). The tracking error is computed as the standard deviation of the excess portfolio return (in excess of the cap-weighted benchmark return). The 95% tracking error is the 95th percentile tracking error from the distribution of rolling window tracking errors. The rolling window tracking errors are computed using a rolling window of one year and a step size of one week. The information ratio is the excess portfolio return (in excess of the cap-weighted benchmark return) divided by the standard deviation of the excess portfolio return (in excess of the cap-weighted benchmark return). We classify quarters with a positive (negative) cap-weighted market return as a bull (bear) quarter. Bull relative return is the geometric average relative return (relative to the cap-weighted benchmark) in bull markets. Bear relative return is the geometric average relative return (relative to the cap-weighted benchmark) in bear markets. For the next metric, we first regress the portfolio excess returns (in excess of the risk-free return) on seven factor returns (market, size, value, momentum, low volatility, high profitability, low investment, all non-market factors are dollar-neutral long/short portfolios). The factor intensity is the sum of the regression coefficients from the following regressors: size, value, momentum, low volatility, high profitability and low investment. The columns indicate the portfolios. Besides the cap-weighted benchmark portfolios for each region, we include two MBMS MBA indices with two different market beta adjustment methods. HFI Multi-Beta Multi-Strategy 6F 4S EW MBA (leverage) combines six factor tilts (size, value, momentum, low volatility, high profitability and low investment, equally weighted), four different weighting schemes (efficient maximum Sharpe ratio, maximum deconcentration, maximum decorrelation and diversified risk-weighted), and uses leverage to adjust the ex-ante market beta to one. HFI Multi-Beta Multi-Strategy 6F 4S EW MBA (overlay) combines the same factor tilts and weighting schemes as above, but employs the overlay method to adjust the market beta to one. All figures are based on returns use daily total returns from 30 June 2008 to 30 June 2018. The data source is the EDHEC-Risk US and developed countries databases. We use the three-month US Treasury bill rate as the risk-free return.

risks in their offerings. It would be beneficial for the whole industry to start a risk conversation between index providers and asset owners. What is the impact of these risks and what does it cost to manage them?

Conclusion

Scientific Beta's multi-smart-factor offering takes account of three essential principles in the construction of multi-factor assembly:

- Decorrelation of the variations in the premia associated with each risk factor. Good management of the decorrelation between the factor returns improves the multi-factor index's probability of outperformance.
- Taking the interactions between the factors into account. This avoids factor intensity being reduced by the residual exposures of each smart factor index.
- Top-down allocation between these smart factor indices. This allocation, which is carried out in a fully transparent way, allows the allocation objectives to be defined and controls the risks to which the investor wishes to be exposed. This risk control imperative also includes the possibility of having risk-control options for non-factor risks.

A simple equal-weighted allocation across the full set of factors in the menu, as embodied by the Multi-Beta Multi-Strategy 6 Factor HFI EW allocation, constitutes a neutral starting point for multi-factor investing, in the absence of a particular objective or preference expressed by the investor. In addition to the equal-weight allocation, Scientific Beta offers its clients a multi-beta allocation solution. This solution can be based on different choices of factors, objectives of absolute or relative risk levels, or factor exposures

These equal-weighted multi-factor indices are offered with important risk-control options, comprising notably sector neutrality and market beta adjustment. These risk control options correspond to veritable fiduciary choices for the investor that Scientific Beta believes are important to offer as an index provider.

This wealth of choices is guided by the fact that we do not believe that investment objectives and constraints are identical for all investors and that is why we believe that the top-down approach, which is a simple and transparent risk allocation that is appropriate for the client's risk objective, is the best approach. Moreover, risk control options allow investors to express explicit preferences in terms of risks, which are often hidden by-products of factor strategies, such as sector and market risk. We understand for example that the sector-neutrality or long-only market-beta-neutrality choices will reduce

13a. Performance and risk measures of MBMS indices with different risk control options, US universe

EDHEC-Risk US LTTR 31 December 1976–31 December 2016

	Cap-weighted benchmark	HFI MBMS 6F 4S EW	HFI MBMS SN 6F 4S EW	HFI MBMS 6F 4S EW MBA (leverage)	HFI MBMS SN 6F 4S EW MBA (leverage)
Annualised average return	10.86%	13.95%	13.66%	15.34%	14.73%
Annualised volatility	17.07%	14.40%	15.28%	17.16%	17.90%
Sharpe ratio	0.35	0.63	0.58	0.61	0.55
P-value	–	<0.1%	<0.1%	<0.1%	<0.1%
Maximum drawdown	54.3%1	48.13%	50.10%	54.16%	55.70%
Relative return	–	3.09%	2.80%	4.48%	3.87%
Tracking error	–	5.10%	3.97%	4.76%	3.99%
95% tracking error	–	9.79%	7.13%	9.16%	7.75%
Information ratio	–	0.61	0.71	0.94	0.97
Maximum relative drawdown	–	33.0%	19.5%	26.4%	15.4%
Bull relative return	–	0.46%	1.34%	5.41%	5.84%
Bear relative return	–	6.67%	4.69%	2.88%	0.91%
Factor intensity	–	0.60	0.42	0.71	0.49

This figure compares Scientific Beta MBMS indices with various risk-control options to the cap-weighted market portfolio. The rows show different portfolio metrics. Annualised average return is the annualised geometric average return. Annualised volatility is the annualised standard deviation of portfolio returns. The Sharpe ratio is computed by dividing the annualised excess portfolio return (in excess of the risk-free rate) by the standard deviation of the excess portfolio return. p-value indicates the p-value of the Ledoit and Wolf (2008) test on the difference in Sharpe ratios between the cap-weighted benchmark and the index indicated in the column. The maximum drawdown is the highest loss from peak to trough in the observation period. Relative return is the geometric average excess portfolio return (in excess of the cap-weighted benchmark return). The tracking error is computed as the standard deviation of the excess portfolio return (in excess of the cap-weighted benchmark return). The 95% tracking error is the 95th percentile tracking error from the distribution of rolling window tracking errors. The rolling window tracking errors are computed using a rolling window of one year and a step-size of one week. The information ratio is the excess portfolio return (in excess of the cap-weighted benchmark return) divided by the standard deviation of the excess portfolio return (in excess of the cap-weighted benchmark return). We classify quarters with a positive (negative) cap-weighted market return as a bull (bear) quarter. Bull relative return is the geometric average relative return (relative to the cap-weighted benchmark) in bull markets. Bear relative return is the geometric average relative return (relative to the cap-weighted benchmark) in bear markets. For the next metric, we first regress the portfolio excess returns (in excess of the risk-free return) on seven factor returns (market, size, value, momentum, low volatility, high profitability, low investment, all non-market factors are dollar-neutral long/short portfolios). Factor intensity is the sum of the regression coefficients from the following regressors: size, value, momentum, low volatility, high profitability, and low investment. The columns indicate the portfolios. Besides the cap-weighted benchmark portfolio, we include four MBMS indices with different risk-control options. HFI Multi-Beta Multi-Strategy 6F 4S EW combines six factor tilts (size, value, momentum, low volatility, high profitability, and low investment, equally weighted) and four different weighting schemes (efficient maximum Sharpe ratio, maximum deconcentration, maximum decorrelation and diversified risk-weighted), and uses the high factor intensity filter for the stock selection. HFI Multi-Beta Multi-Strategy SN 6F 4S EW combines the same factor tilts, weighting schemes, and the HFI filter as above but uses a sector neutral stock selection. HFI Multi-Beta Multi-Strategy 6F 4S EW MBA (leverage) combines six factor tilts (size, value, momentum, low volatility, high profitability and low investment, equally weighted), four different weighting schemes (efficient maximum Sharpe ratio, maximum deconcentration, maximum decorrelation and diversified risk-weighted), and uses leverage to adjust the ex-ante market beta to one. HFI Multi-Beta Multi-Strategy SN 6F 4S EW MBA (leverage) combines the same factor tilts and weighting schemes, and uses the same market beta adjustment as above, but employs the sector-neutral rules for the stock selection. All figures are based on returns use daily total returns from 31 December 1976 to 31 December 2016. The data source is the EDHEC-Risk US LTTR database. The cap-weighted index is based on the 500 largest stocks by market capitalisation in the US. We use the three-month US Treasury bill rate as the risk-free return.

13b. Performance and risk measures of MBMS indices with different risk control options, developed universe

Developed universe 18 June 2004–30 June 2018

	Cap-weighted benchmark	HFI MBMS 6F 4S EW	HFI MBMS SN 6F 4S EW	HFI MBMS 6F 4S EW MBA (leverage)	HFI MBMS SN 6F 4S EW MBA (leverage)
Annualised average return	7.82%	11.13%	11.03%	12.86%	12.32%
Annualised volatility	15.49%	13.42%	13.80%	15.84%	15.99%
Sharpe ratio	0.42	0.74	0.71	0.73	0.69
P-value	–	<0.1%	<0.1%	<0.1%	<0.1%
Maximum drawdown	57.13%	49.79%	49.94%	55.97%	55.91%
Relative return	–	3.31%	3.21%	5.05%	4.50%
Tracking error	–	3.21%	2.71%	2.69%	2.34%
95% tracking error	–	6.80%	5.68%	4.68%	4.13%
Information ratio	–	1.03	1.18	1.88	1.92
Maximum relative drawdown	–	8.12%	7.29%	5.69%	5.72%
Bull relative return	–	0.87%	1.21%	5.46%	5.03%
Bear relative return	–	6.81%	6.00%	3.91%	3.22%
Factor intensity	–	0.34	0.64	0.92	0.76

This figure compares Scientific Beta MBMS indices with various risk-control options to the cap-weighted market portfolio. The rows show different portfolio metrics. Annualised average return is the annualised geometric average return. Annualised volatility is the annualised standard deviation of portfolio returns. The Sharpe ratio is computed by dividing the annualised excess portfolio return (in excess of the risk-free rate) by the standard deviation of the excess portfolio return. p-value indicates the p-value of the Ledoit and Wolf (2008) test on the difference in Sharpe ratios between the cap-weighted benchmark and the index indicated in the column. The maximum drawdown is the highest loss from peak to trough in the observation period. Relative return is the geometric average excess portfolio return (in excess of the cap-weighted benchmark return). The tracking error is computed as the standard deviation of the excess portfolio return (in excess of the cap-weighted benchmark return). The 95% tracking error is the 95th percentile tracking error from the distribution of rolling window tracking errors. The rolling window tracking errors are computed using a rolling window of one year and a step-size of one week. The information ratio is the excess portfolio return (in excess of the cap-weighted benchmark return) divided by the standard deviation of the excess portfolio return (in excess of the cap-weighted benchmark return). We classify quarters with a positive (negative) cap-weighted market return as a bull (bear) quarter. Bull relative return is the geometric average relative return (relative to the cap-weighted benchmark) in bull markets. Bear relative return is the geometric average relative return (relative to the cap-weighted benchmark) in bear markets. For the next metric, we first regress the portfolio excess returns (in excess of the risk-free return) on seven factor returns (market, size, value, momentum, low volatility, high profitability, low investment, all non-market factors are dollar-neutral long/short portfolios). Factor intensity is the sum of the regression coefficients from the following regressors: size, value, momentum, low volatility, high profitability, and low investment. The columns indicate the portfolios. Besides the cap-weighted benchmark portfolio, we include four MBMS indices with different risk-control options. HFI Multi-Beta Multi-Strategy 6F 4S EW combines six factor tilts (size, value, momentum, low volatility, high profitability, and low investment, equally weighted) and four different weighting schemes (efficient maximum Sharpe ratio, maximum deconcentration, maximum decorrelation and diversified risk-weighted), and uses the high factor intensity filter for the stock selection. HFI Multi-Beta Multi-Strategy SN 6F 4S EW combines the same factor tilts, weighting schemes, and the HFI filter as above but uses a sector neutral stock selection. HFI Multi-Beta Multi-Strategy 6F 4S EW MBA (leverage) combines six factor tilts (size, value, momentum, low volatility, high profitability and low investment, equally weighted), four different weighting schemes (efficient maximum Sharpe ratio, maximum deconcentration, maximum decorrelation and diversified risk-weighted), and uses leverage to adjust the ex-ante market beta to one. HFI Multi-Beta Multi-Strategy SN 6F 4S EW MBA (leverage) combines the same factor tilts and weighting schemes, and uses the same market beta adjustment as above, but employs the sector-neutral rules for the stock selection. All figures are based on returns use daily total returns from the inception date of the market-beta-adjusted indices at 18 June 2004 to 30 June 2018. The data source is the EDHEC-Risk developed countries database. The cap-weighted index is based on 1,470 stocks from 23 developed countries (Austria, Australia, Belgium, Canada, Denmark, Finland, France, Germany, Greece [before June 2015], Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, South Korea [before June 2015], Spain, Sweden, Switzerland, UK and US). We use the three-month US Treasury bill rate as the risk-free return.

relative risks (with respect to the reference CW benchmark) to the detriment of the reduction in absolute risks, whether involving volatility or maximum drawdown. Ultimately, a single optimal solution does not exist because investors are not identical after all.

References

Aguet, Daniel, Noël Amenc and Felix Goltz (2018). Managing Sector Risk in Factor Investing. ERI Scientific Beta White Paper.

Amenc, Noël, Frédéric Ducoulombier, Mikheil Esakia, Felix Goltz and Sivagaminathan Sivasubramanian (2017). Accounting for Cross-Factor Interactions in Multifactor Portfolios without Sacrificing Diversification and Risk Control. *Journal of Portfolio Management.*

Amenc, Noël, and Felix Goltz (2013). Smart Beta 2.0. *Journal of Index Investing* 4(3).

Amenc, Noël, Felix Goltz and Ashish Lodh (2018). Mind the Gap: On the Importance of Understanding and Controlling Market Risk in Smart Beta Strategies. *Journal of Portfolio Management* 44(4): 60–70.

Amenc, Noël, Felix Goltz and Sivagaminathan Sivasubramanian (2015). Robustness of Smart Beta Strategies. *Journal of Index Investing* 6(1): 17–38.

Amenc, Noël, Felix Goltz and Sivagaminathan Sivasubramanian (2017). Investability of Scientific Beta Indices. Scientific Beta White Paper.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing and Xiaoyan Zhang (2006). The Cross-Section of Volatility and Expected Returns. *Journal of Finance* 61(1): 259–299.

Asness, Clifford S. (1992). Changing Equity Risk Premia and Changing Betas over the Business Cycle. Working Paper, University of Chicago.

Banz, Rolf W. (1981). The Relationship Between Return and Market Value of Common Stocks. *Journal of Financial Economics* 9(1): 3–18.

Carhart, M. M. (1997). On Persistence of Mutual Fund Performance. *Journal of Finance* 52(1): 57–82.

Chung, Kee H., and Hao Zhang (2014). A Simple Approximation of Intraday Spreads Using Daily Data. **Journal of Financial Markets** 17, 94–120.

Cohen, Randolph B., Christopher Polk and Tuomo Vuolteenaho (2003). The Value Spread. *Journal of Finance* 58(2): 609–41.

Fama, Eugene F., and Kenneth R. French (2012). Size, Value, and Momentum in International Stock Returns. *Journal of Financial Economics* 105(3): 457–72.

Fama, Eugene F., and Kenneth R. French (1992). The Cross-Section of Expected Stock Returns. *Journal of Finance* 47(2): 427–465.

Harvey, Campbell R. (1989). Time-Varying Conditional Covariances in Tests of Asset Pricing Models. *Journal of Financial Economics* 24(2): 289–317.

Harvey, Campbell R., Yan Liu and Heqing Zhu (2016). … And the Cross-Section of Expected Returns. *Review of Financial Studies* 29(1): 5–68.

Hou, Kewei, Chen Xue and Lu Zhang (2015). Digesting Anomalies: An Investment Approach. *Review of Financial Studies* 28(3): 650–705.

Ilmanen, Antti, and Jared Kizer (2012). The Death of Diversification Has Been Greatly Exaggerated. *Journal of Portfolio Management* 38(3): 15–27.

14. Multi-beta multi-strategy with and without MBA and sector-neutral options

	Scientific Beta US HFI MBMS 6F 4S EW			Scientific Beta Developed HFI MBMS 6F 4S EW		
Relative annual performance	No risk control	Sector-neutral	Sector-neutral and MBA (leverage)	No risk control	Sector-neutral	Sector-neutral and MBA (leverage)
2018 (up to 30 June)	–1.47%	0.76%	0.87%	–0.41%	0.83%	0.85%
2017	–1.36%	-0.09%	2.48%	0.77%	1.43%	4.32%
2016	–0.16%	1.61%	3.30%	0.13%	1.39%	2.61%
2015	2.01%	1.58%	1.79%	4.06%	3.89%	4.18%
2014	4.02%	1.60%	2.67%	4.77%	3.41%	4.00%
2013	1.04%	1.61%	5.62%	1.75%	1.30%	5.51%
2012	–0.51%	0.65%	3.49%	–0.32%	–0.15%	3.30%
2011	5.49%	1.94%	2.33%	6.09%	3.60%	3.27%
2010	5.14%	4.69%	6.27%	6.84%	6.17%	8.48%
2009	–1.12%	1.39%	4.31%	–2.70%	–2.16%	2.08%

This figure shows Scientific Beta MBMS indices with and without risk control options for the US and developed markets. The rows indicate years and the columns show the portfolios. No Risk Control corresponds to the HFI Multi-Beta Multi-Strategy 6F 4S EW index which combines six factor tilts (size, value, momentum, low volatility, high profitability and low investment, equally weighted) and four different weighting schemes (efficient maximum Sharpe ratio, maximum deconcentration, maximum decorrelation and diversified risk-weighted), and applies the high factor intensity filter to the stock selection. Sector-neutral combines the same factor tilts, weighting schemes, and the HFI filter as above but uses a sector-neutral stock selection. Sector-neutral and MBA (leverage) combines the same factor tilts and weighting schemes and uses the same sector-neutral stock selection as above, but employs leverage to adjust the ex-ante market beta to one. Relative returns are returns in excess of the respective cap-weighted benchmark return. All figures are based on total returns. The data source is the EDHEC-Risk US and developed countries databases.

Jegadeesh, Narasimhan, and Sheridan Titman (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *Journal of Finance* 48(1): 65–91.

Ledoit, Oliver, and Michael Wolf (2008). Robust Performance Hypothesis Testing with the Sharpe Ratio. *Journal of Empirical Finance* 15(5): 850–59.

Martellini, Lionel, and Philippe Priaulet (2002). Competing Methods for Option Hedging in the Presence of Transaction Costs. *Journal of Derivatives* 9(3): 26–38.

Merton, Robert (1980). On Estimating the Expected Return on the Market: An Exploratory Investigation. *Journal of Financial Economics* 8: 323–361.

Novy-Marx, Robert (2013). The Other Side of Value: The Gross Profitability Premium. *Journal of Financial Economics* 108(1): 1–28.

Managing sector risk in factor investing

Sector risk is an implicit bet investors take when investing in smart factor indices that can have a material impact on short-term performance.

Investors looking to manage these short-term risks can use the sector-neutral risk control option offered by Scientific Beta since the launch of its platform in 2013. It is an effective approach to reducing short-term relative losses since it significantly reduces tracking error as well as extreme relative statistics such as maximum relative drawdown and extreme tracking error.

Nevertheless, sector-neutrality comes with costs because it reduces the distance of weights between the smart factor index and the CW index. This implies a reduction in factor intensity and an increase in volatility that negatively impact the long-term risk-adjusted performance.

The choice of using the sector-risk-control option is a trade-off between investors' aversion to short-term risks generated by sector risk and their willingness to harvest factor risk premia in the most efficient way, to achieve the highest risk-adjusted performance over the long run.

Daniel Aguet, Deputy Research Director, ERI Scientific Beta; **Noël Amenc**, Associate Dean for Business Development, EDHEC Business School, CEO, ERI Scientific Beta; **Felix Goltz**, Head of Applied Research, EDHEC-Risk Institute, Research Director, ERI Scientific Beta

Sector risk is an implicit bet investors take when investing in smart factor indices. Even if it is not a priced risk factor in the cross-section of expected returns, sector risk can nevertheless have a material impact on short-term performance. In this article, we review the sector-risk-control option offered to investors by Scientific Beta that has been available on its platform since its launch in 2013. More specifically, we examine the two complementary approaches to managing sector risk, which are stock selection and sector-neutral allocation. We compare long- and short-term risk-adjusted performance as well as factor exposures of smart factor indices with and without the sector risk control option on long-term data, covering several

decades to assess its impact. We then illustrate the short-term consequences that sector risk can have on relative performance. We eventually conclude that the choice of using the sector risk control option is a trade-off between investors' aversion to short-term risks generated by sector risk and their willingness to harvest factor risk premia in the most efficient way, to achieve the highest risk-adjusted performance over the long run.

Implicit sector risks in smart factor indices

Common smart factor indices give explicit exposures to priced risk factors that should provide good long-term risk-adjusted performance. However, they are also known to expose investors to a number of hidden or implicit risks, as documented in a recent Scientific Beta white paper (Shirbini [2018]). In particular, investors expose themselves to an implicit bet on market beta, given that most smart factor indices have a market beta below one. Other implicit risks are macroeconomic risks and sector or country risks. In this article, we will focus on the implicit sector risk taken by smart factor indices and will try to understand the implications on their short- and long-term risk-adjusted performance. We will also discuss possibilities to avoid sector risks through appropriate risk control options, in particular the sector-neutrality constraints introduced in Amenc and Goltz (2013)[1], which have been available on the Scientific Beta index platform since its launch in 2013. Our analysis in this article extends the earlier analysis of Amenc et al (2015), which analysed the benefits of sector-neutrality constraints in value factor indices.

Smart factor indices have time-varying sector-relative allocations compared to the cap-weighted (CW) index. It is well known that, for instance, the low volatility factor tends to overweight sectors like utilities and non-cyclical consumer goods, while it underweights riskier sectors. In the case of the low volatility factor, these relative allocations are fairly stable through time, as seen in figure 1. However, we also see that for the high momentum factor, these relative allocations vary much more through time. It is therefore evident that sectors, even if they are not priced in the cross-section of expected returns, can nevertheless have an important impact on the short-term performance of smart factor indices that might negatively affect investors. This is why sector-neutrality is very often used in the asset management industry, especially for investors who need tracking error control, which is the case for most institutional investors.

In the rest of this article, we focus on a comparison between standard smart factor indices and their sector-neutral counterparts. Our key findings are that sector-neutrality adds value in terms of reducing tracking error and short-term underperformance of the CW reference index, but also comes with costs in the form of higher volatility and lower factor intensity. Moreover, the sector-neutrality objective naturally reduces the distance of strategy weights to market capitalisation weights, which may not be suitable for investors who are looking for a pronounced difference with CW indices. Given these trade-offs, the most appropriate solution depends on investor preferences. It is precisely the objective of Scientific Beta's Smart Beta 2.0 framework to allow investors to make such explicit choices, not just on the targeted factors but also on additional risk control options.

The remainder of this article is organised as follows. In the second section, we explain the two complementary approaches to control sector risk in factor investing. In the third section, we perform an analysis between standard smart factor indices (with no sector-neutral objective) and sector-neutral smart factor indices on absolute risk-adjusted performance. In the fourth section, we analyse their differences in terms of factor exposures. In the fifth section, we analyse their relative risk-adjusted performance and show the short-term risk that can arise from sector exposures. Finally, we draw the conclusions of this article.

Two complementary approaches to control sector risk

There are two important aspects that investors should take into account to control sector risk in factor investing, which are i) stock selection to maintain proper sector diversity and ii) sector-neutral allocation as a risk management tool. We will discuss these aspects in more detail in this section.

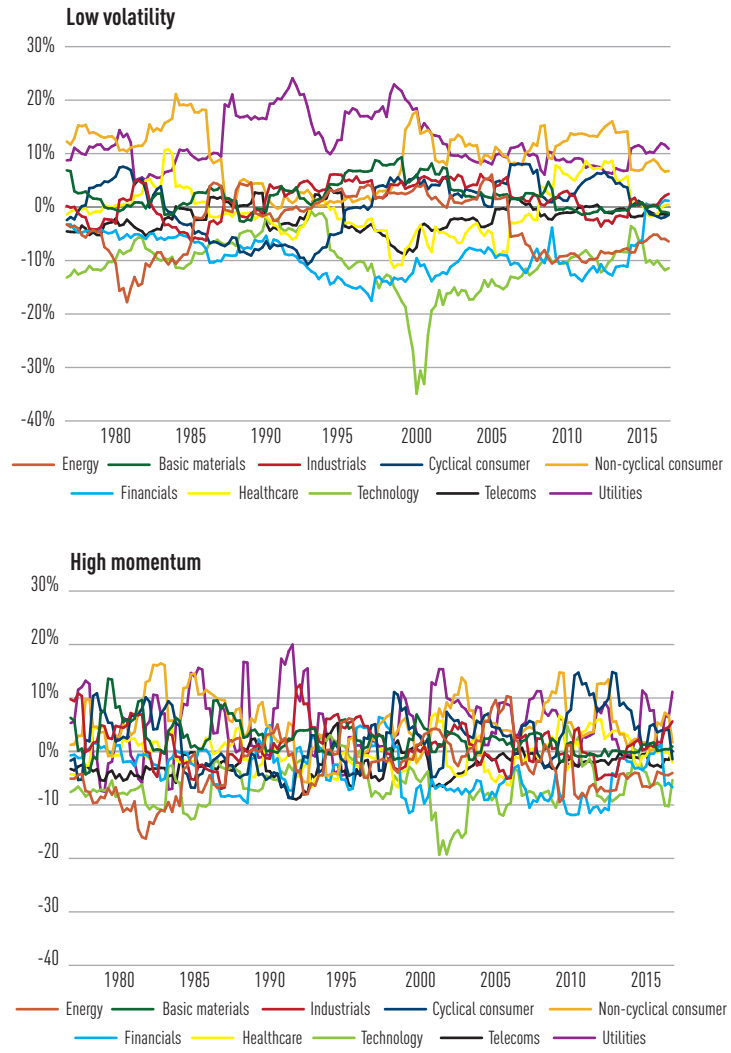
Stock selection

In the academic literature, stock selection is carried out on the whole universe, sometimes with the exclusion of financial companies, as in Fama and French (1993) and Novy-Marx (2013), or treated separately in two different selections (see Novy-Marx [2012]).

It is well known that some risk factors have persistent biases towards some sectors, like the low volatility or value factors, or like momentum, which can be very concentrated when a few sectors outperform or underperform the stock market. A first approach to control sector risk is to avoid concentration in a few sectors by maintaining a proper level of sector diversity through an appropriate stock selection process.

1 See in particular exhibit 5 in Amenc and Goltz (2013), which analyses the performance of a smart beta index with and without the use of the sector-neutrality option.

1. Historical relative sector allocation of the EDHEC-Risk Long-Term US HFI Low Volatility and High Momentum Diversified Multi-Strategy (4-Strategy) smart factor indices



The data are based on quarterly sector allocations from 31 December 1976 to 31 December 2016. The low volatility smart factor is the EDHEC-Risk Long-Term United States High-Factor-Intensity Low Volatility Diversified Multi-Strategy (4-Strategy) and the high momentum smart factor is the EDHEC-Risk Long-Term United States High-Factor-Intensity Low Volatility Diversified Multi-Strategy (4-Strategy). The CW index is the EDHEC-Risk Long-Term United States Cap-Weighted index. The relative allocation is computed as the difference between sector allocations of smart factors minus the sector allocation of the CW index.

There are two very similar approaches used in the academic literature to tackle this issue. The first one consists in selecting stocks from the whole universe, but stock scores are adjusted by the mean sector score, as in Novy-Marx (2012). The second approach consists in selecting stocks directly in sectors, as in Moskowitz and Grinblatt (2002), Banko et al (2006) and Asness et al (2014). These two approaches are very similar in terms of maintaining proper sector diversity, but we favour the latter, which is more direct and guarantees the same relative number of stocks in each sector.

Another important argument for carrying out stock selection by taking sectors into account is linked to the comparability of accounting quantities. Indeed, accounting quantities can be affected by specific sector characteristics that can make them difficult to compare across sectors. This, in turn, might lead to concentration in a few stocks and thus to a lack of sector diversity in the stock selection. This is especially the case for the value, low investment and high profitability risk factors, which are all based on accounting measures.

Financial leverage, intangibles and off-balance sheet items are the three main elements that can make accounting quantities difficult to compare across sectors. Directly adjusting the accounting measures is an alternative to sector-relative stock selection, but we will argue that accounting adjustments are not desirable, based on a range of examples.

A first example is financial leverage (ie, the financing of assets through debt). It can make stocks difficult to compare, particularly when comparing financial stocks against those from other sectors. It is well known that value firms are typically high-leverage firms. Many practitioners adjust the book-to-market value for leverage and only include the value firms that are not highly

levered. However, the relevance of such adjustments lacks academic consensus, and the proposed adjustments will lead to greater dependency on accounting information needed to make the adjustments.

A second example is the often-suggested premise that the accounting treatment of certain off-balance sheet quantities (such as leases, R&D expenditure or intangible assets such as 'goodwill') might not capture the true value of the firm's assets if they are not taken into account, leading to less robust value stock selection. Given the dematerialisation of the economy, this poor integration can lead to poor representation of information technology or biotechnology companies in factor selections, for which the factor proxy could be strongly impacted by these accounting discrepancies. Concerning intangible assets, the academic literature questions the validity of several well-known adjustments and suggests that the simple book-to-market variable is a more robust measure of value. For off-balance sheet items like leases, it has been shown by Damodaran (1999) that the book value of equity remains unaffected by leases, as both assets and liabilities change by the same amount. Finally, R&D expenditure is known to capture intangible asset creation – see Gu (2016), Franzen et al (2007), Chan et al (2001) and Lev and Sougiannis (1996, 1999). The value of R&D capital is hard to determine and depreciation rates are hard to justify. Moreover, the major industry that is affected is technology, where R&D expenditure is typically significant and its accounting treatment is different compared to other sectors.

From both the academic and practitioner literature on the adjustment of accounting quantities, we can conclude that there is no consensus on their nature and that the results relating to these adjustments are highly sample-dependent. It therefore seems obvious that stock selection within sectors is a more robust approach and is more consistent with the academic literature.

At Scientific Beta, we already carry out the stock selection for the value, low investment and profitability factors on our standard indices (with no control of sector risk) with a stock selection that takes into account three mega sectors (non-financial/non-tech, non-financial/tech, and financial) to deal with the comparability of accounting measures. The sector-neutrality option will lead to an even more stringent approach, where the stock selection is conducted separately in each sector.

Sector-neutral allocation

The objective of the sector-neutral allocation is to have direct control over sector risk by rescaling the weights of the smart factor to obtain the same sector allocation as the CW index. This is clearly a risk management approach since the goal is to reduce the distance between the sector weights of the smart factor index and the CW sector weights in order to be less dependent on specific short-term sector shocks.

Novy-Marx (2013), in a long/short framework, uses industry indices to make sure that each long stock position is hedged out for industry exposure by taking an offsetting position in the corresponding stock's value-weighted industry portfolio. In a long-only setting, the equivalent way of hedging out sector risk is to ensure a sector-neutral allocation between the smart factor sector weights and the corresponding CW weights by rescaling the stock weights of the smart factor index.

Asness et al (2014) construct an industry-neutral low-risk factor (BAB) in a long/short framework where each industry is market-beta-neutral ex-ante. This is an alternative to sector-neutral allocation that makes sense for the low-risk factor, because the long and short legs have significantly different levels of risk. However, the problem with this approach is that it involves the use of leverage, which is difficult to implement for many institutional investors in a long-only framework; therefore we do not favour it.

Sector-neutral indices

Overall, when stock selection within sectors and sector-neutral allocation are put together, they allow the construction of sector-neutral smart factor indices that maintain proper sector diversity and hedge out most of the sector risk. It nevertheless raises the question of whether these sector-neutral risk factors can still deliver a significant risk premium over the long run. We found evidence in the academic literature that sector-neutral risk factors do still provide significant long-term risk-adjusted performance as seen in Banko et al (2006), Novy-Marx (2013) and Asness et al (2014).

At Scientific Beta, we offer sector-neutral indices that incorporate both approaches discussed above. Indeed, we carry out the stock selection within each of the 10 sectors defined as the economic sectors of the Thomson-Reuters Business Classification. We also rescale weights against the CW index in order to achieve sector-neutral allocation. Note that sector-neutral allocation is not perfectly achieved since we apply turnover and liquidity rules after the weight rescaling, which are used to maintain a high level of replicability of our indices. In the next sections, the sector-neutral smart factor indices we present are based on this technology.

Impact of sector risk on absolute performance

Sector-neutrality reduces the distance between the allocation of the smart factors and the CW index. This is in total opposition to the objective of smart factor investing, which consists in having the highest distance to the CW index allocation to benefit from two sources of added value, which are long-term exposures to rewarded risk factors that are not present in the CW index, and good diversification of specific risks. This implies allocations that are very different to those proposed by the CW index, which is concentrated in stocks with the highest capitalisations and does not take stock correlations into account. Therefore, we expect that sector-neutral smart factors will generate lower Sharpe ratios than their standard counterparts, with an increase in volatility.

In figure 2, we show the absolute statistics of the EDHEC-Risk Long-Term US HFI Diversified Multi-Strategy (4-Strategy) smart factor indices for the six well-known academic risk factors as well as the multi-beta index that incorporates all risk factors on an equally-weighted basis. We also show the same smart factor indices, but with the sector-neutral-control option. Standard smart factor indices exhibit strong outperformance over the CW index, with lower volatilities and higher returns resulting in Sharpe ratios being between 60% and 80% higher.

On the other hand, sector-neutral smart factor indices, as expected, suffer from higher volatilities compared to their standard counterparts, resulting in lower Sharpe ratios, with the exception of mid-cap, which exhibits a slightly higher Sharpe ratio with sector-neutrality control. Volatilities are increased by an average of 6%, ranging from 1% for high profitability to 10% for low volatility, and they are statistically different from standard indices. Returns are fairly similar. We observe that they are higher for mid-cap and value with sector-neutrality but slightly lower for the other smart factors.

Overall, sector-neutrality strongly decreases the distance from CW measure by an average of 60%. This reduction is an indicator of the potential loss of the added value that a smart factor index can provide in terms of improved risk-adjusted performance. Indeed, the closer the distance from CW measure is to zero, the lower the potential to improve risk-adjusted performance compared to the CW index. Thus, investors who seek high value-added potential with their smart beta strategies, and thus require a clear deviation or 'active share', might not find sector-neutrality constraints suitable.

2. Comparative annual statistics and sector deviations between standard and sector-neutral EDHEC-Risk Long-Term US HFI Diversified Multi-Strategy (4-Strategy) smart factor indices

31 December 1976–31 December 2016 (RI/$)

	CW	Mid-cap	Value	High momentum	Low volatility	High profitability	Low investment	MBMS
Standard smart factors								
Annualised returns	10.86%	14.08%	13.36%	14.38%	13.70%	13.84%	14.00%	13.95%
Annualised volatility	17.07%	14.96%	14.83%	15.48%	13.33%	15.25%	14.17%	14.40%
Sharpe ratio	0.35	0.62	0.57	0.62	0.67	0.59	0.65	0.63
Distance from CW	–	53%	59%	46%	64%	64%	54%	48%
Sector-neutral smart factors								
Annualised returns	10.86%	14.79%	13.57%	13.99%	13.03%	13.20%	13.14%	13.66%
Annualised volatility	17.07%	15.91%	15.60%	16.27%	14.62%	15.43%	15.31%	15.28%
Sharpe ratio	0.35	0.63	0.56	0.56	0.56	0.54	0.54	0.58
Distance from CW	–	16%	20%	23%	25%	22%	20%	17%
Volatility difference	–	**–0.95%**	**–0.77%**	**–0.79%**	**–1.29%**	**–0.18%**	**–1.14%**	**–0.88%**
P-value	–	0.02%	0.02%	0.02%	0.02%	2.36%	0.02%	0.02%
Sharpe ratio difference	–	0.01	–0.01	–0.05	–0.10	–0.05	**–0.10**	–0.05
P-value	–	79.9%	77.8%	20.6%	7.3%	24.8%	0.7%	11.9%

The analysis is based on daily total returns in US dollarsfrom 31 December 1976 to 31 December 2016. All statistics are annualised. Yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. Coefficients significant at 5% p-value are highlighted in bold. The distance from CW measure is the quarterly average of the sum of absolute differences between individual weights of the smart factor and the CW index. P-value for the Sharpe ratio or volatility differences are computed using the methodology described in Ledoit and Wolf (2008, 2011). The smart factor indices used are the EDHEC-Risk Long-Term United States High-Factor-Intensity Mid-Cap Diversified Multi-Strategy (4-Strategy), EDHEC-Risk Long-Term United States High-Factor-Intensity Value Diversified Multi-Strategy (4-Strategy), EDHEC-Risk Long-Term United States High-Factor-Intensity High Momentum Diversified Multi-Strategy (4-Strategy), EDHEC-Risk Long-Term United States High-Factor-Intensity Low Volatility Diversified Multi-Strategy (4-Strategy), EDHEC-Risk Long-Term United States High-Factor-Intensity High Profitability Diversified Multi-Strategy (4-Strategy), EDHEC-Risk Long-Term United States High-Factor-Intensity Low Investment Diversified Multi-Strategy (4-Strategy), EDHEC-Risk Long-Term United States High-Factor-Intensity Diversified Multi-Beta Multi-Strategy (MBMS) 6-Factor 4-Strategy EW and their sector-neutral counterparts.

Impact of sector risk on factor exposures

Because it forces their allocations to be closer to the CW index, the factor exposures of smart factors are affected in the same way. Since the sector-neutral smart factor has closer allocations to the CW index, it will have a smaller loading on its desired tilt. This implies that sector-neutrality will automatically decrease factor intensity. On the positive side, the market beta exposure should be improved for the same reason and we should expect sector-neutral smart factors to have market beta closer to 1, which provides them with better conditional performance and a reduction in relative risk associated with the market beta gap that exists between the CW index and smart factor indices.

In figure 3, we show the factor exposures of the standard and sector-neutral versions of EDHEC-Risk Long-Term US HFI Multi-Strategy smart factor indices. Several comments can be drawn from this figure.

First, we note that the market beta exposures of standard smart factor indices are lower than one. This is a typical defensive characteristic of smart factor indices and is one of the implicit risks documented by Shirbini (2018), but they increase when using the sector-neutrality option, with a notable difference for low volatility.

Next, we examine the exposure of smart factors to their desired factor tilt. For standard indices, mid-cap has the lowest exposure with 0.17, whereas value has the highest with 0.27. Sector-neutral smart factors exhibit lower factor exposure to their desired factor tilt with the exception of mid-cap. Low investment exposure diminishes by 20%, from 0.19 to 0.15. Value exposure falls by 25%, from 0.27 to 0.20. For momentum, its exposure is decreased by 30% from 0.21 to 0.14. Finally, for low volatility and high profitability, their exposures to their desired tilts fall by 50%. Remember that these two smart factors have the highest distance to CW measures in their standard version. The case of the mid-cap smart factor is interesting, since its exposure to its desired tilt is slightly higher with sector-neutrality, but we note a considerable reduction in exposures to the other factors, leading to lower factor intensity.

There is also another notable difference in the overall factor intensity between the standard and sector-neutral versions of the smart factor indices. The factor intensity of the standard smart factor indices is the highest for value with 0.73 and lowest for high profitability with 0.49. In the case of the sector-neutral versions, factor intensity is reduced for all smart factors by an average of 28%. The reduction is stronger for high momentum, with a decrease of 38%. Low volatility and high profitability have reductions that are close to the average despite the considerable decrease in the exposure to their desired tilts. This reduction in factor intensity is explained by the closer allocation of the sector-neutral smart factors to the CW index, which implies that returns are explained more by the market beta than by risk factors.

3. Factor exposures of standard and sector-neutral EDHEC-Risk Long-Term US HFI Diversified Multi-Strategy (4-Strategy) smart factor indices

31 December 1976–31 December 2016 (RI/$)

	CW	Mid-cap	Value	High momentum	Low volatility	High profitability	Low investment	MBMS
Standard smart factors								
CAPM market beta	**1.00**	**0.87**	**0.85**	**0.90**	**0.73**	**0.90**	**0.82**	**0.85**
Annualised unexplained	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00
Market beta	**1.00**	**0.85**	**0.84**	**0.89**	**0.73**	**0.89**	**0.82**	**0.84**
SMB* beta	0.00	**0.17**	**0.08**	**0.09**	**0.06**	**0.09**	**0.07**	**0.09**
HML* beta	0.00	**0.14**	**0.27**	**0.09**	**0.06**	0.01	0.09	0.11
MOM* beta	0.00	**0.02**	**0.08**	**0.21**	0.00	**–0.02**	**0.03**	**0.06**
Low volatility* beta	0.00	**0.08**	**0.05**	**0.09**	**0.24**	**0.13**	**0.09**	**0.11**
High profitability* beta	0.00	**0.10**	**0.12**	**0.08**	**0.11**	**0.22**	**0.10**	**0.12**
Low investment* beta	0.00	**0.10**	**0.11**	**0.05**	**0.06**	**0.05**	**0.19**	**0.10**
R-squared	100.0%	91.5%	92.4%	93.6%	92.0%	94.6%	94.4%	95.5%
Factor intensity	0.00	0.62	0.73	0.61	0.53	0.49	0.57	0.59
Factor drift	0.00	0.24	0.25	0.22	0.19	0.17	0.16	0.18
Sector-neutral smart factors								
CAPM market beta	**1.00**	**0.92**	**0.92**	**0.94**	**0.84**	**0.90**	**0.90**	**0.90**
Annualised unexplained	0.00	0.01	0.01	0.01	0.00	0.01	0.00	0.01
Market beta	**1.00**	**0.89**	**0.91**	**0.93**	**0.84**	**0.90**	**0.89**	**0.89**
SMB* beta	0.00	**0.18**	**0.08**	**0.07**	**0.05**	**0.06**	**0.06**	**0.08**
HML* beta	0.00	**0.10**	**0.20**	**0.07**	**0.05**	**0.04**	**0.10**	**0.09**
MOM* beta	0.00	**0.05**	**0.07**	**0.14**	0.01	**0.02**	**0.02**	**0.05**
Low volaility* beta	0.00	0.00	–0.01	**0.02**	**0.11**	**0.05**	**0.01**	**0.03**
High profitability* beta	0.00	**0.06**	**0.12**	**0.06**	**0.11**	**0.11**	**0.09**	**0.09**
Low investment* beta	0.00	**0.07**	**0.10**	0.01	**0.07**	**0.06**	**0.15**	**0.08**
R-squared	100.0%	91.4%	94.3%	93.5%	94.0%	94.9%	94.9%	96.3%
Factor intensity	0.00	0.46	0.56	0.38	0.39	0.33	0.44	0.43
Factor drift	0.00	0.23	0.21	0.21	0.19	0.18	0.19	0.17

The analysis is based on daily total returns in US dollars from 31 December 1976 to 31 December 2016. All statistics are annualised. Yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. The regression is based on weekly total returns. The market factor is the excess return series of the CW index over the risk-free rate. The other six factors are equal-weighted daily-rebalanced factors obtained from Scientific Beta and are beta-adjusted every quarter with their realised CAPM beta. Coefficients significant at 5% p-value are highlighted in bold. The smart factor indices used are the EDHEC-Risk Long-Term United States High-Factor-Intensity Mid-Cap Diversified Multi-Strategy (4-Strategy), EDHEC-Risk Long-Term United States High-Factor-Intensity Value Diversified Multi-Strategy (4-Strategy), EDHEC-Risk Long-Term United States High-Factor-Intensity High Momentum Diversified Multi-Strategy (4-Strategy), EDHEC-Risk Long-Term United States High-Factor-Intensity Low Volatility Diversified Multi-Strategy (4-Strategy), EDHEC-Risk Long-Term United States High-Factor-Intensity High Profitability Diversified Multi-Strategy (4-Strategy), EDHEC-Risk Long-Term United States High-Factor-Intensity Low Investment Diversified Multi-Strategy (4-Strategy), EDHEC-Risk Long-Term United States High-Factor-Intensity Diversified Multi-Beta Multi-Strategy 6-Factor 4-Strategy EW and their sector-neutral counterparts.

Impact of sector risk on relative risk and performance

For now, we have focused on the impact of sector-neutrality on smart factor indices in terms of absolute risk-adjusted returns and conclude that they were negatively impacted because of the loss of factor intensity. However, as mentioned before, sector-neutrality is also a way of controlling for relative risk. Sector-neutral smart factors should therefore have lower tracking errors. In figure 4, we show the relative statistics of the EDHEC-Risk Long-Term US HFI Diversified Multi-Strategy (4-Strategy) standard and sector-neutral smart factor indices. We first observe that standard smart factor indices have relative returns that are fairly similar, in the range of 2.5% to 3.5%, whereas the tracking errors are much more scattered, ranging from 4.9% for high profitability to 7% for low volatility. Information ratios are therefore strongly positive, with 0.67 for high momentum and 0.41 for low volatility.

As expected, sector-neutral smart factor indices exhibit lower tracking errors. The reduction ranges from –4% for the mid-cap to –32% for the low volatility smart factors compared to their standard counterparts. Moreover, we show that these reductions are statistically significant at the 1% level, which clearly indicates that sector-neutrality is definitely helpful in decreasing relative risks. We highlight that the maximum relative drawdown measure is also reduced with sector-neutrality by an average of 30%, with 48% for mid-cap and 17% for high momentum. An interesting measure of extreme risk is the 10-year rolling worst 5% tracking error, which is also reduced by an average of 23% across the different smart factors.

While relative returns are very similar, we importantly observe that information ratios are higher compared to standard smart factors, although these differences are not statistically significant. The probability of outperformance at a one, three and five-year horizon is increased for mid-cap, value, high momentum and the multi-beta multi-strategy indices.

Overall, we can conclude that sector-neutrality is important for controlling relative risks, since the decreases in tracking errors are statistically significant, but when we look at relative risk-adjusted performance, there is no real impact and information ratios are fairly similar.

We conclude this section by focusing on the analysis of live indices. In figure 5, we show the one-year calendar relative returns as well as absolute and relative statistics for the last 10 years for the SciBeta US HFI Diversified MBMS 6F 4S EW index, the SciBeta Developed ex-US HFI Diversified MBMS 6F 4S EW index, and their sector-neutral counterparts. We first highlight the differences that can arise in yearly relative returns as in 2016, 2017 and 2018 for SciBeta US smart factor indices. This is a clear demonstration of short-term risks that can affect smart factor indices and the usefulness of sector neutrality.

Second, we observe that yearly relative returns of sector-neutral smart factors are more stable compared to their standard counterparts, which is confirmed by their lower tracking errors. This can also be illustrated by the fact that, for instance, on the SciBeta US universe, the standard smart factor index posted five negative years out of 11 whereas the sector-neutral smart factor posted only one negative relative return over the same period. Moreover, this is in line with the improved probability of outperformance statistics observed in figure 4.

Nevertheless, the better stability of relative returns comes at a cost.

4. Comparative relative statistics between standard and sector-neutral EDHEC-Risk Long-Term US HFI smart factor indices

31 December 1976–31 December 2016 (RI/$)

	CW	Mid-cap	Value	High momentum	Low volatility	High profitability	Low investment	MBMS
EDHEC-Risk LTTR US HFI smart factor index								
Annualised relative returns	–	3.22%	2.50%	3.52%	2.84%	2.98%	3.14%	3.09%
Annualised tracking error	–	6.34%	5.71%	5.23%	7.01%	4.87%	5.65%	5.10%
Information ratio	–	0.51	0.44	0.67	0.41	0.61	0.56	0.61
Maximum relative drawdown	–	38.6%	41.8%	13.2%	47.3%	27.2%	33.2%	33.0%
10-year rolling tracking error worst 5%	–	8.1%	8.8%	7.8%	10.9%	6.9%	8.6%	7.6%
Outperformance probability (1Y)	–	66.7%	67.1%	69.8%	65.2%	72.7%	69.7%	70.6%
Outperformance probability (3Y)	–	73.7%	78.7%	83.4%	77.0%	84.7%	81.1%	81.4%
Outperformance probability (5Y)	–	77.4%	75.5%	90.2%	81.7%	89.8%	87.0%	87.1%
EDHEC-Risk LTTR US HFI smart factor sector-neutral index								
Annualised relative returns	–	3.93%	2.71%	3.13%	2.17%	2.34%	2.28%	2.80%
Annualised tracking error	–	6.06%	4.62%	4.53%	4.78%	4.31%	4.46%	3.97%
Information ratio	–	0.65	0.59	0.69	0.45	0.54	0.51	0.71
Maximum relative drawdown	–	20.0%	31.2%	10.9%	29.0%	21.3%	26.4%	19.5%
10-year rolling tracking error worst 5%	–	7.2%	6.6%	6.4%	6.8%	5.8%	6.5%	5.5%
Outperformance probability (1Y)	–	74.0%	69.0%	70.1%	63.9%	67.9%	65.8%	71.5%
Outperformance probability (3Y)	–	80.1%	78.8%	86.0%	70.9%	74.3%	75.3%	80.5%
Outperformance probability (5Y)	–	81.8%	80.0%	91.4%	78.3%	76.6%	83.0%	82.3%
Tracking error difference		**–0.28%**	**–1.09%**	**–0.69%**	**–2.23%**	**–0.57%**	**–1.18%**	**–1.13%**
P-value		0.12%	0.02%	0.02%	0.02%	0.02%	0.02%	0.02%
Information ratio difference		0.14	0.15	0.02	0.05	-0.07	-0.05	0.10
P-value		12.95%	16.33%	76.39%	65.21%	60.41%	81.40%	23.98%

The analysis is based on daily total returns in US dollars from 31 December 1976 to 31 December 2016. Yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. Coefficients significant at 5% p-value are highlighted in bold. P-value for the Information ratio difference and tracking error difference are computed using the methodology described in Ledoit and Wolf (2008, 2011). The smart factor indices used are the EDHEC-Risk Long-Term United States High-Factor-Intensity Mid-Cap Diversified Multi-Strategy (4-Strategy), EDHEC-Risk Long-Term United States High-Factor-Intensity Value Diversified Multi-Strategy (4-Strategy), EDHEC-Risk Long-Term United States High-Factor-Intensity High Momentum Diversified Multi-Strategy (4-Strategy), EDHEC-Risk Long-Term United States High-Factor-Intensity Low Volatility Diversified Multi-Strategy (4-Strategy), EDHEC-Risk Long-Term United States High-Factor-Intensity High Profitability Diversified Multi-Strategy (4-Strategy), EDHEC-Risk Long-Term United States High-Factor-Intensity Low Investment Diversified Multi-Strategy (4-Strategy), EDHEC-Risk Long-Term United States High-Factor-Intensity Diversified Multi-Beta Multi-Strategy (MBMS) 6-Factor 4-Strategy EW and their sector-neutral counterparts.

Indeed, sector-neutral smart factor indices have a higher level of absolute volatility. This is due to the reduction of the distance between the allocation of the smart factors and the CW index. This reduction in distance goes against the objective of factor investing, which consists in having the highest distance to the CW index allocation to benefit from two sources of added value, namely long-term exposures to rewarded risk factors and good diversification of specific risks. The direct consequence of this distance reduction is a deterioration in Sharpe ratios.

It is clear from the different examples we provide that sectors can have a strong impact on the short-term performance and relative risks of smart factor indices, even if these effects should not be persistent over the long term, since sector risk is not priced into the cross-section of expected returns. It is important, however, for investors to understand these implicit risks and the different ways of dealing with them and their implications.

5. One-year calendar relative returns and absolute and relative statistics for the SciBeta US HFI Diversified MBMS 6-Factor 4-Strategy EW index, the SciBeta Developed ex-US HFI Diversified MBMS 6-Factor 4-Strategy EW index and their sector-neutral counterparts

	SciBeta US HFI Diversified MBMS 6F 4S EW		SciBeta Developed ex-US HFI Diversified MBMS 6F 4S EW	
Years	Standard	Sector-neutral	Standard	Sector-neutral
2018 (31 July)	–1.55%	0.89%	0.39%	0.44%
2017	–1.36%	–0.09%	3.83%	3.60%
2016	–0.16%	1.61%	0.49%	0.99%
2015	2.01%	1.58%	6.55%	6.72%
2014	4.02%	1.60%	5.45%	5.15%
2013	1.04%	1.61%	2.38%	0.90%
2012	–0.51%	0.65%	-0.01%	–0.81%
2011	5.49%	1.94%	6.76%	5.16%
2010	5.14%	4.69%	8.32%	7.48%
2009	–1.12%	1.39%	–4.26%	-5.56%
2008	6.55%	4.40%	7.43%	7.16%
Annualised tracking error	4.24%	3.46%	4.18%	3.83%
Information ratio	0.53	0.62	0.97	0.92
Annualised volatility	17.56%	18.34%	15.74%	15.92%
Sharpe ratio	0.59	0.55	0.39	0.35

The analysis is based on daily total returns in US dollars from 31 December 2007 to 31 December 2018. The return of the 2018 calendar year is the year-to-date return without annualisation, otherwise all statistics are annualised. Yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. The smart factor indices used are the SciBeta US High-Factor-Intensity Diversified Multi-Beta Multi-Strategy 6-Factor 4-Strategy EW, the SciBeta Developed ex-US High-Factor-Intensity Diversified Multi-Beta Multi-Strategy 6-Factor 4-Strategy EW and their sector-neutral counterparts.

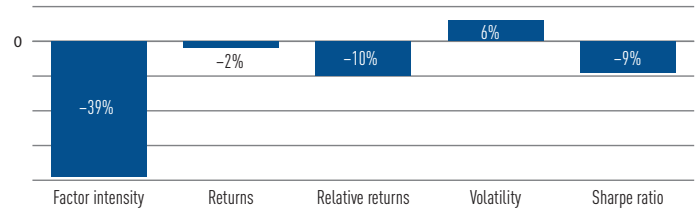
Conclusion

The objective of smart factor investing is to obtain the highest distance to the CW index allocation to benefit from two sources of added value, namely long-term exposures to rewarded risk factors and good diversification of specific risks. This is efficiently achieved through our standard smart factor offering, which delivers significant long-term risk-adjusted performance. Nevertheless, we showed in this article that sector risk, which is one of the several implicit risks taken when investing in smart factor indices, can be very high. Indeed, deviations from the CW sector weights can be important and very persistent through time and this can lead to short-term underperformance for investors that might be undesirable.

Investors looking to manage these short-term risks can use the sector-neutral risk-control option offered on Scientific Beta indices. Using the sector-neutral risk option has a clear advantage in terms of relative risk-adjusted performance since information ratios are increased. We also showed that it is an effective approach to reducing short-term relative losses since it significantly reduces tracking error as well as extreme relative statistics such as maximum relative drawdown and extreme tracking error.

Nevertheless, sector-neutrality comes with costs. Indeed, the reduction of the distance from CW weights implies two very important consequences for long-term risk-adjusted performance. These consequences are shown in figure 6, which reports the percentage change of key metrics when moving from the standard to the sector-neutral version of a multi-smart factor index. First, there is a clear reduction in factor intensity. Since exposures to risk factors are the key drivers of performance in smart factor investing, this may be undesirable for some investors. Second, there is a considerable increase in the level of absolute risk (volatility). These two elements lead to a reduction in the long-term absolute risk-adjusted performance (Sharpe ratio) of sector-neutral smart factor indices compared to their standard counterparts. These trade-offs imply that the choice of the most suitable version of the index depends on investor preferences.

6. Costs of sector-neutral smart factor indices compared to their standard counterparts in terms of factor intensity, returns, relative returns, volatility and Sharpe ratio



The analysis is based on total returns in US dollars from 31 December 1976 to 31 December 2016. The cost is the relative difference between the sector-neutral index and the standard index (percentage change). The smart factor indices used are the EDHEC-Risk Long-Term US High-Factor-Intensity Diversified Multi-Beta Multi-Strategy (MBMS) 6-Factor 4-Strategy EW and its sector-neutral counterpart.

Managing hidden risks – a practical case

As documented in a recent Scientific Beta white paper (Shirbini [2018]), smart factor indices are known to expose investors to a number of hidden risks that can have a negative impact on short-term performance. In particular, investors expose themselves to a market beta gap and to sector and geographical risks amongst others. We will explain how Scientific Beta tackles these hidden risks and assess the benefits for investors of controlling them.

Geographical risk

Smart factor selection, done on an index like the SciBeta Developed index, which contains seven regional blocks, can lead to significant regional weight deviations compared to the reference CW index (the SciBeta Developed regional blocks are the US, euro-zone, UK, Japan, Canada, Developed Asia-Pacific ex-Japan and Developed Europe ex-Euro/UK). There is no academic evidence that taking on geographical risk is rewarded in the long term and it has been shown that factor investing works best within economically integrated regions (Fama and French [2012]).

For these two reasons, Scientific Beta constructs all its regional indices in a way that ensures regional block neutrality compared to the reference CW index. Indeed, we first construct regional block smart factor indices that are then weighted according to their corresponding free-float market capitalisation in the regional reference CW index.

Sector risk

Smart factor indices have time-varying sector-relative allocations compared to their reference CW index. There is no academic evidence that sector risk is rewarded over the long term, but it might negatively affect the short-term performance of smart factor indices.

Scientific Beta offers investors a sector risk control option which combines i) stock selection within sectors to maintain sector diversity and ii) sector-neutral allocation to ensure neutrality of weights compared to the reference CW index.

Market beta adjustment

The market beta of smart beta strategies is an implicit result of various construction choices. Most smart beta offerings have a market beta that is uncontrolled and often lower than one due to the defensive bias of some factors and weighting schemes. This has two direct consequences for investors. First, they are not fully capturing the long-term equity market risk premium. Second, the short-term performance of smart factor indices might be negatively impacted, since market exposure has a direct influence the conditional performance of smart factor indices in bull and bear markets.

Scientific Beta offers investors a market beta adjustment option using either leverage or an overlay using futures. The leverage option consists in varying the allocation to the smart factor index and cash to target an ex-ante beta of one. The overlay option consists in using futures to target an ex-ante market beta of one. Both approaches have a constraint on cash borrowing of 30%.

Combining these risk options allows investors to remove important hidden risks simultaneously and therefore helps them to smooth out their relative performance, thereby reducing their short-term risk of underperformance.

In figure A, we show the last 10 years of annual performance of the SciBeta Developed HFI Diversified Multi-Beta Multi-Strategy 6-Factor 4-Strategy EW index with and without the combined risk options (sector-neutrality and market beta adjustment). We first observe that over the last 10 years, the index without the risk control option underperformed its reference CW index three times. Second, its annual performance ranges between –2.7% and 6.8%. Third, its performance over the last three years is particularly disappointing. There are three main reasons for this. First, the performance over the last three years of the US market was driven by the concentration of the CW index in the largest stocks, and notably GAFA (Google, Apple, Facebook and Amazon) stocks, which penalised diversified indices such as ours. Second, our index had a negative relative weight to the technology sector, which outperformed the reference CW index over the period. Third, the index CAPM market beta over the last three years was 0.87. Since we were in a bull market, the index was clearly penalised by its defensive characteristic.

The benefits of the sector-neutral and market beta adjustment risk options using either the leverage or overlay versions are quite clear. First, both indices posted only positive relative returns over the last 10 years. Second, their relative returns are more stable over the period, since annual performance ranges between 1.36% and 8.48% for the leveraged version and between 1.27% and 7.63% for the overlay version. Third, their performance over the last three years is much more interesting since they are not impacted by the market beta gap and technology sector underexposure of the underlying index. We note that the leveraged version produces better relative returns, since it allows the characteristics of the underlying index to be preserved, whereas the use of futures in the overlay version only adds exposure to the market beta without any exposure to long-term rewarded risk factors. Investors that can use leverage should favour the leveraged version compared to the overlay version. Both indices achieve dramatic improvements in short-term performance relative to the standard index, which does not embed either of the two risk control options. It should be noted that the differences in performance come about even though these indices seek exposure to the same set of smart beta factors.

The benefits highlighted above are clearly visible in the relative statistics in figure B. Information ratios are improved by a factor of two thanks to an increase in relative returns and a reduction in tracking errors. Max relative drawdowns are reduced by more than 30%. This is a clear demonstration of the better management of short-term risks. However, these benefits come at the cost of lower absolute risk-adjusted performance because of higher absolute risks. Indeed, we observe that the absolute volatilities are increased by 20% and Sharpe ratios are decreased by more than 10%. We also note an increase in extreme risks, since maximum drawdown statistics are increased by 15%.

This practical case highlights the importance of considering optional risk adjustments, such as controlling sector and market risk, when choosing to be exposed to factors. This choice is a trade-off investors have to make between their aversion to short-term risks generated by hidden risks embedded in standard smart factor indices, which can lead to short-term losses relative to the CW index, and their willingness to harvest factor risk premia in the most efficient way and to achieve the highest risk-adjusted performance over the long run.

A. Annual performance of the SciBeta Developed HFI Diversified MBMS 6-Factor 4-Strategy EW with and without sector risk and market beta adjustment control option

Years	Standard	Sector-neutral + MBA (leverage)	Sector neutral + MBA (overlay)
2018 (18 September)	–0.74%	1.36%	1.27%
2017	0.77%	4.32%	3.88%
2016	0.13%	2.61%	2.237%
2015	4.06%	4.18%	3.71%
2014	4.77%	4.00%	3.67%
2013	1.75%	5.51%	4.80%
2012	–0.32%	3.30%	2.84%
2011	6.09%	3.27%	2.90%
2010	6.84%	8.48%	7.63%
2009	–2.70%	2.08%	1.65%

The analysis is based on daily total returns in US dollars from 31 December 2008 to 18 September 2018. The return of the 2018 calendar year is the year-to-date return without annualisation, otherwise all statistics are annualised. The smart factor indices used are the SciBeta Developed High-Factor-Intensity Diversified Multi-Beta Multi-Strategy 6-Factor 4-Strategy EW, SciBeta Developed High-Factor-Intensity Diversified Multi-Beta Multi-Strategy (Sector Neutral) 6-Factor 4-Strategy EW Market Beta Adjusted (leverage) and SciBeta Developed High-Factor-Intensity Diversified Multi-Beta Multi-Strategy (sector-neutral) 6-Factor 4-Strategy EW Market Beta Adjusted (overlay).

B. Absolute and relative performance over the last 10 years of the SciBeta Developed HFI Diversified MBMS 6-Factor 4-Strategy EW with and without sector risk and market beta adjustment control option

	SciBeta Developed CW index	Standard	Sector-neutral + MBA (leverage)	Sector-neutral + MBA (overlay)
Return	7.58%	10.42%	11.24%	10.85%
Volatility	16.88%	14.46%	17.36%	17.28%
Sharpe ratio	0.43	0.70	0.63	0.61
Maximum drawdown	47.50%	41.30%	47.50%	47.50%
Relative return	–	2.84%	3.66%	3.27%
Tracking error	–	3.48%	2.30%	2.02%
Information ratio	–	0.82	1.59	1.61
Maximum relative drawdown	–	8.10%	5.70%	5.00%

The analysis is based on daily total returns in US dollars from 31 August 2008 to 31 August 2018. The return of the 2018 calendar year is the year-to-date return without annualisation, otherwise all statistics are annualised. The smart factor indices used are the SciBeta Developed High-Factor-Intensity Diversified Multi-Beta Multi-Strategy 6-Factor 4-Strategy EW, SciBeta Developed High-Factor-Intensity Diversified Multi-Beta Multi-Strategy (Sector Neutral) 6-Factor 4-Strategy EW Market Beta Adjusted (leverage) and SciBeta Developed High-Factor-Intensity Diversified Multi-Beta Multi-Strategy (sector-neutral) 6-Factor 4-Strategy EW Market Beta Adjusted (overlay).

To provide further analysis of the difference between the standard index and its sector-neutral version, we conduct an analysis of the return difference over time. Figure 7 shows the three-year and 10-year rolling outperformance of the standard EDHEC-Risk Long-Term US HFI Diversified Multi-Beta Multi-Strategy 6-Factor 4-Strategy EW index versus its sector-neutral counterparts. The probability of outperformance of the standard index is 64% for the three-year rolling window and 60% for the 10-year rolling window. This is consistent with the considerable reduction in factor intensity observed with sector-neutrality and shows the superiority of the standard smart factors over sector-neutral ones in producing higher returns over the long run. It is also clear from figure 7 that return differences between the two versions are relatively minor over a 10-year horizon, but can be pronounced over a three-year horizon. We can see, for example, that the period of the late 1990s was marked by pronounced underperformance of the standard version over its sector-neutral counterpart, as sector deviations were a drag on performance. However, in the following years, sector-neutrality became a drag on performance, with the standard index posting its most pronounced outperformance over the sector-neutral version. For such shorter horizons, the impact of a choice concerning sector-neutrality is considerable.

Overall, the decision on whether or not to use the sector-neutral option is a fiduciary choice for investors. This choice is a trade-off between their aversion to short-term risks generated by sector risk embedded in standard smart factor indices, which can lead to short-term losses relative to the CW index, and their willingness to harvest factor risk premia in the most efficient way and to achieve the highest risk-adjusted performance over the long run.

7. Three-year and 10-year rolling outperformance of standard versus sector-neutral EDHEC-Risk Long-Term US HFI Diversified MBMS 6-Factor 4-Strategy EW smart factor indices

The analysis is based on three-year and 10-year rolling weekly total returns in US dollars from 31 December 1976 to 31 December 2016. The smart factor indices used are the EDHEC-Risk Long-Term US HFI Diversified Multi-Beta Multi-Strategy (MBMS) 6-Factor 4-Strategy EW index and its sector-neutral counterpart.

The role of technology and utility sector exposures in factor strategies

It is instructive to consider examples from particular time periods to understand the impact of sector risks. We will show through three examples that sector risks can lead to significant short-term underperformance that sector-neutrality can help reduce.

For the purpose of illustration, we will focus on two smart factors that are known to have persistent over/underexposures to some specific sectors. For the first example (figure A), we show the performance of the low volatility smart factor index, which is known to be underexposed to the technology sector. In 1999, the sector outperformed the CW index by more than 77%, whereas the underexposure of the smart factor was close to –19% on average. The standard low volatility smart factor posted a negative performance of –2.8% and underperformed the CW index in 1999 by –26%, whereas its sector-neutral version posted a positive performance of 6.4% and underperformed the CW index by –16%. It is also important to highlight that the maximum relative drawdown, which measures the maximum relative loss of a strategy compared to its benchmark, is reduced by more than 50%. The annual tracking error of the sector-neutral smart factor is also reduced compared to the standard version.

For the second example (figure B), we show the performance of the value smart factor index, which has a persistent overexposure to the utilities sector. In 2015, the sector underperformed the CW index by –6.7%, whereas the overexposure of the smart factor index was close to +7%. The standard value smart factor underperformed the CW index in 2012 by –3.5%, whereas its sector-neutral version underperformed the CW index by –2.4%, a reduction of more than 30%. The maximum relative drawdown and the annual tracking error of the sector-neutral smart factor index are also reduced compared to the standard version.

For the last example (figure C), we show that the use of the sector-neutrality option in 2017 and 2018 would have been beneficial to investors, because those two years were marked by outstanding performance of the technology sector. We observe that the technology sector index outperformed the SciBeta US CW index by 19% from the beginning of 2017 to the end of June 2018. The standard SciBeta US HFI Diversified MBMS 6-Factor 4-Strategy EW, which was underexposed to the sector by an average of –13%, underperformed the CW index by –2%, whereas its sector-neutral version outperformed it by +0.5%.

A. Year 1999 absolute and relative statistics of EDHEC-Risk Long-Term US Broad and Technology CW index and EDHEC-Risk Long-Term US HFI Low Volatility Diversified Multi-Strategy (4-Strategy) standard and sector-neutral smart factor indices

1999 (RI/$)	EDHEC-Risk Long-Term US CW index		EDHEC-Risk Long-Term US HFI Low Volatility Diversified Multi-Strategy (4-Strategy) index	
	Broad	Technology	Standard	Sector-neutral
Annualised returns	22.87%	77.23%	–2.82%	6.37%
Annualised volatility	18.39%	31.61%	12.17%	13.76%
Sharpe ratio	0.98	2.29	na	0.11
Annualised relative returns	–	54.4%	–25.7%	–16.5%
Annualised tracking error	–	19.0%	12.8%	8.7%
Information ratio	–	2.86	na	na
Maximum relative drawdown	–	12.4%	23.2%	14.8%

The analysis is based on daily total returns in US dollars from 31 Dec ember 1998 to 31 Dec ember 1999. All statistics are annualised. Yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. The smart factor indices used are the EDHEC-Risk Long-Term US HFI Low Volatility Diversified Multi-Strategy (4-Strategy) and its sector-neutral counterparts.

B. Year 2015 absolute and relative statistics of EDHEC-Risk Long-Term US Broad and Utilities CW index and EDHEC-Risk Long-Term US HFI Value standard and sector-neutral smart factor indices

2015 (RI/$)	EDHEC-Risk Long-Term US CW index		EDHEC-Risk Long-Term US HFI Low Value Diversified Multi-Strategy (4-Strategy) index	
	Broad	Utilities	Standard	Sector-neutral
Annualised returns	0.83%	–6.66%	–2.70%	–1.56%
Annualised volatility	5.37%	17.32%	14.20%	14.43%
Sharpe ratio	0.05	na	na	na
Annualised relative returns	–	–7.5%	–3.5%	–2.4%
Annualised tracking error	–	15.0%	3.8%	3.1%
Information ratio	–	na	na	na
Maximum relative drawdown	–	18.3%	6.5%	5.2%

The analysis is based on daily total returns in US dollars from 31 December 2014 to 31 December 2015. All statistics are annualised. Yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. The smart factor indices used are the EDHEC-Risk Long-Term US High-Factor-Intensity Value Diversified Multi-Strategy (4-Strategy) and its sector-neutral counterparts.

C. Relative performance of the standard and sector-neutral SciBeta US HFI Diversified MBMS 6-Factor 4-Strategy EW index

31 December 2015–30 June 2018	Technology CW index	Standard MBMS	Sector-neutral MBMS
Annualised relative returns	18.8%	–2.0%	0.5%
Annualised tracking error	7.9%	3.1%	2.5%
Information ratio	2.39	na	0.20
Maximum relative drawdown	5.43%	4.39%	1.63%

The analysis is based on daily total returns in USD from 31-Dec-2016 to 30-Jun-2018. All statistics are annualised. Yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. The smart factor indices used are the SciBeta US HFI Diversified Multi-Beta Multi-Strategy (MBMS) 6-Factor 4-Strategy EW and its sector-neutral counterparts. The technology CW index is the SciBeta US Technology Cap-Weighted index.

In terms of risk budgeting, it also involves investors knowing whether they want to minimise absolute or relative risks and this choice should probably be considered from a broader perspective than a simple investment in equity factors (ie, in a risk management framework for all of their asset classes).

For ERI Scientific Beta, in line with its status as an index provider, its single and multi-factor index offering (with or without the sector-neutrality option) offers investors and their asset managers the possibility to exercise this fiduciary option.

References

Amenc, N., and F. Goltz (2013). Smart Beta 2.0. *Journal of Index Investing* 4(3): 15–23.

Amenc, N., F. Goltz, S. Sivasubramanian and A. Lodh. 2015. Robustness of Smart Beta Strategies. Journal of Index Investing 6(1): 17-38.

Asness, C., A. Frazzini and L.H. Pedersen (2014). Low-Risk Investing without Industry Bets. *Financial Analysts Journal* 70(4): 24–41.

Banko, J., M. Conover and G. Jensen (2006). The Relationship between the Value Effect and Industry Affiliation. Journal of Business 79(5): 2595–616.

Chan, K.C., J. Lakonishok and T. Sougiannis (2001). The Stock Market Valuation and Research and Development Expenditures. *Journal of Finance* 56(6): 2431–2456.

Damodaran, A. (1999). Dealing with Operating Leases in Valuation. NYU Research Paper Series.

Fama, E., and K. French (1993). Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics* 33(1): 3–56.

Fama, E.F., and K.R. French (2012). Size, Value, and Momentum in International Stock Returns. *Journal of Financial Economics* 105(3): 457–72.

Franzen, L.A., K.J. Rodgers and T.T. Simon (2007). Measuring Distress Risk: The Effect of R&D Intensity. *Journal of Finance* 62(6): 2931–67.

Gu, L. (2016). Product Market Competition, R&D Investment, and Stock Returns. *Journal of Financial Economics* 119(2): 441–455.

Ledoit, O., and M. Wolf (2008). Robust Performance Hypothesis Testing With the Sharpe Ratio. *Journal of Empirical Finance* 15(5): 850–859.

Ledoit, O., and M. Wolf (2011). Robust Performance Hypothesis Testing With the Variance. *Wilmott Magazine* 55(4): 86–89.

Lev, B., and T. Sougiannis (1996). The Capitalization, Amortization, and Value-Relevance of R&D. *Journal of Accounting and Economics* 21(1): 107–138.

Lev, B., and T. Sougiannis (1999). Penetrating the Book-to-Market Black Box: The R&D Effect. *Journal of Business Finance & Accounting* 26(3–4): 419–449.

Moskowitz, T. J., and M. Grinblatt (2002). Do Industries Explain Momentum? *Journal of Finance* 54(4): 1249–1290.

Novy-Marx, R. (2012). Quality Investing. Working paper.

Novy-Marx, R. (2013). The Other Side of Value: The Gross Profitability Premium. *Journal of Financial Economics* 108(1): 1–28.

Shirbini, E. (2018). Misconceptions and Mis-selling in Smart Beta: Improving the Risk Conversation in the Smart Beta Space. ERI Scientific Beta White Paper (February).

Managing macroeconomic risks in smart beta portfolios:

From beta to regime premia diversification

Mikheil Esakia, Quantitative Research Analyst, ERI Scientific Beta; **Felix Goltz**, Head of Applied Research, EDHEC-Risk Institute, Research Director, ERI Scientific Beta

The cyclicality of equity factor premia is driven by changes in the economic environment.

Different factors can have similar exposure to the macro environment. Thus, balancing factor exposures may not lead to good diversification across macro regimes.

Our analysis shows that value and momentum factors are pro-cyclical, while size is counter-cyclical, and 'quality' factors do not show pronounced sensitivity to business cycles.

We design portfolios to achieve performance that is more balanced across different macro regimes.

It is well established that equity factors such as size, valuation, momentum, low risk, profitability and investment lead to positive premia over the long term. However, there is also extensive evidence that factor premia vary over time, and may experience long periods of underperformance (Harvey [1989], Asness [1992]). Knowing that these different sources of returns are not perfectly correlated, it is intuitive to tilt towards multiple factors to diversify the possible underperformance of factor(s) and smooth returns across time.

Yet there is no consensus on how to allocate optimally across multiple factors. Given the limited understanding we have about the underlying drivers of the risk premia, naïvely diversifying across different factors is often chosen as a practical solution. Making sure that exposures to different factors are balanced is seen as a sign of diversification. This however ignores that two different factors could depend on similar macroeconomic drivers. If economic conditions deteriorate, a portfolio that is balanced across factors with similar exposure to these conditions will be poorly diversified.

The academic literature strongly suggests that at least some of the equity factors are proxies for the state variables such as term structure (Petkova [2006]), default risk (Vassalou and Xing [2004]), future economic growth (Liu and Zhang [2008]), etc. Theoretical foundations and the empirical evidence together are what motivate our research to identify the economic mechanisms behind factor premia. The aim of this study is to shed more light on the drivers of the cyclicality of premia. We provide new insights that may help to better understand the cyclicality and improve allocation decisions. Accounting for similar dependencies on the economic conditions will ultimately improve the diversification of a multi-factor allocation. Our analysis can also have implications for market risk management, such as avoiding exposure to factors with increasing market betas during unfavourable economic conditions.

Unsurprisingly, this study is not the first that analyses the cyclicality of equity factors across macroeconomic environments. Many providers of factor products have considered this issue.[1] However, these studies lack a clear economic justification for their definition of macro environments, and widely disagree on how a given factor reacts in these environments. Our analysis is different because we justify our definition of macroeconomic states with an economic rationale and a large body of evidence in the academic literature.

The rest of the article is organised as follows. We first provide the motivation for the link between economic states and the factor risk premia. Next, we review some of the existing studies in this area from practitioners. We then discuss conceptual considerations regarding selection of relevant variables and propose a methodology for classifying macroeconomic regimes. Finally, we analyse conditionality of factor premia to the macro regimes and give illustrative examples for implications for factor investors.

Why should business cycles matter for factor premia?

Macroeconomic environment as key determinant of asset prices

To capture the conditional behaviour of factor returns, we need to consider the macroeconomy more broadly and move beyond the impact of stock market cycles. Of course, we could simply consider how factors behave in bull and bear markets. However, conditioning solely on market returns could be misleading.

1 See, eg, Ilmanen, Maloney and Ross (2014), Gupta et al (2014), Ung and Luk (2016), Devarajan et al (2016).

Consider the period following the recent global financial crisis. The drawdown in equity markets was followed by very strong rebound in early 2009. However, such strong returns mainly reflected that the economy was in a very bad state since the Lehman bankruptcy in September 2008, stock market valuations were depressed, and future expected returns were high to compensate investors for risk. Thus, what appears as a 'good time' ex-post when looking at stock market returns was a 'bad time' ex-ante (see Petkova and Zhang [2005]). Fama (1981) and Stock and Watson (1999) argue that realised market returns is indeed a noisy measure of economic conditions.

Moreover, stock market returns do not fully capture the economic conditions that an average investor cares about most. Most investors are employed and own houses, small businesses and other non-marketed assets along with stocks and bonds. Consequently, aggregate stock returns could be a poor proxy for the return on aggregate wealth, which is the opportunity set of ultimate interest to the representative investor (Roll [1977]). Equilibrium asset-pricing theory suggests that the average investor would like to hedge against business cycle risks. Assuming a multi-period world, current demand on assets is affected by the possibility of changes in future investment opportunities (Merton [1973]). In short, factor investors care about how their factors fare when economic conditions or investment opportunities change.

There is strong evidence that equity factors are indeed affected by economic conditions. Factors deliver risk premia, which are explained precisely by the fact that these factors tend to have poor returns in bad times when the state of the economy is poor. Economists refer to such states as times with high marginal utility of consumption. In such bad times, the required premium for bearing risk is high. Economists call this phenomenon counter-cyclical variation of risk premia.[2] The variation of risk premia depends on business cycle variables. The premia for equity factors likewise varies with business cycle variables, as has been shown in a large number of studies. For example, Hahn and Lee (2006), Petkova (2006) and Petkova and Zhang (2005) suggest that the size and value factors are exposed to business cycle risks. Liu and Zhang (2008) show that about half of the profits of the momentum factor are due to its dependence on future economic activity. A similar dependence of factor premia on business cycle variables has been documented for the low risk factor (Cederburg and Doherty, 2016) and momentum.

Overall, both theory and empirical evidence indicate that equity factors are linked to the macroeconomic environment. Understanding these links is thus crucial for risk transparency of equity factor portfolios.

Understanding cyclicality ≠ factor timing

A clarification is in order. Note that we are not trying to time factors using information about the economic states. What we are looking at is the contemporaneous relationship between factor returns and indicators that closely track business cycles. A contemporaneous relationship does not allow timing decisions. For timing, we would need to identify a predictive link between the macro environment and factor returns. Such a link is unlikely since asset prices usually incorporate information much faster than reported GDP or other 'slow-moving' variables. If anything, we would expect that factor returns might predict economic fundamentals, not vice-versa. In fact, a study by Liew and Vassalou (2000) shows that returns of equity factors such as size and value can predict GDP growth.

To illustrate that a contemporaneous link between the macro environment and equity factors does not allow timing, we consider a simple illustration. We look at the relationship between changes in macroeconomic state variables and factor returns. Figure 1 reports differences between factor returns when the changes in the respective state variable were in the top and bottom quartiles. The results indicate that the low risk factor performed significantly better during the times when the contemporaneous changes in default spread were in the lowest quartile, compared to the highest quartile. We now try to predict changes in default spread based on an econometric model composed of other macro state variables. If we use the predicted changes in default spread, the relationship reverts and becomes insignificant. We can observe the same effect if we look at momentum and changes in the term spread. Even though the negative sensitivity of momentum does not disappear, the relationship becomes highly uncertain with a p-value of greater than 50%.

Our objective is not to shed light on timing decisions, but rather to analyse how factors behave in different macroeconomic environments, and to show how such information can help improve diversification for factor investors.

Measuring sensitivity to the economic state

Selecting macroeconomic state variables

A key decision in defining macroeconomic regimes is to select the relevant state variables. Relevant macroeconomic indicators must fulfil a set of indicators, if they are to be useful in analysing factor cyclicality.

The first criterion is that macro state variables need to be sufficiently fast-moving to capture changes in expectations contemporaneously with factor returns. Relying on 'slow-moving' realised economic quantities such as growth and inflation will not fulfil this criterion. However, there are fast-moving variables that capture information about macroeconomic expectations. For example, Geske and Roll (1983) find that bond and stock investors realise the future changes in fiscal and monetary policy, and adjust prices and interest rates accordingly without a delay.[3] Beyond empirical findings, economic theory suggests that fast-moving variables, such as the dividend yield, short rate, credit spread and term spread, should capture expectations about economic fundamentals. For example, the basic dividend discount model of Gordon (1962) suggests that the aggregate dividend yield reflects the expected equity premium and the future dividend growth in the economy. Likewise, models of monetary policy suggest that short interest rates will reflect inflation expectations, the output gap and macroeconomic policy shocks (eg, Ang [2014]). Our objective is thus to define macroeconomic regimes based on fast-moving indicators.

The second criterion is that our state variables have been identified as leading indicators of economic conditions. State variables should be related to future macroeconomic activity (eg, industrial production). They should also be related to the future equity market premium (stock market excess return). A positive relationship with the aggregate market premium can be interpreted as a negative relationship with risk tolerance, as a high expected premium reflects low risk tolerance. Ultimately, this second requirement means that the relevant state variables capture information about expectations about the market premium and economic activity, similar to leading indicators used by economists.

A third criterion is that a link between the macroeconomic variable and equity factor returns have been identified in the finance literature. Of course, selecting state variables for which there is no link with factor returns is meaningless for factor investors.

Based on the above-mentioned requirements and solid evidence from the academic literature, we have identified four state variables. These are the level and the slope of the yield curve, default spread and dividend yield. Figure 2 briefly summarises the theory behind why these variables should matter, and how they would reflect economic outlook and risk-tolerance. Dividend yield is more related to the risk tolerance of the investors, while the term structure and default spread carry information about both risk tolerance

1. Understanding cyclicality ≠ factor timing

US December 1979–December 2016	Momentum	Low risk
Change in default spread (Q4-Q1)	-5.9%	–15.3%
p-value	56.5%	2.0%
Predicted change in default spread (Q4-Q1)	1.3%	**4.9%**
p-value	99.4%	**64.0%**
Change in term spread (Q4-Q1)	–30.0%	–9.9%
p-value	0.2%	16.4%
Predicted change in term spread (Q4-Q1)	**–17.3%**	–2.0%
p-value	**50.3%**	91.3%

The reported figures are differences between conditional annualised returns in extreme quartiles of conditioning variables, which are the changes in term spread and default spread. The returns for momentum and low risk come from K. French and AQR data libraries, respectively. The term spread is 10-year minus one-year Treasury bond yields. The default spread is Moody's Baa minus Aaa corporate yields. The predicted change in each variable is computed as a difference between predicted level and current level. The levels at month t are predicted with OLS method, predictive variables being levels of four state variables at time t–1. The parameters are estimated each month since April 1953, using expending windows. The four state variables are short-term interest rates (3-month T-bills), term spread, default spread and 12-month trailing dividend yield on CRSP value-weighted index.

2. Theory and empirical evidence for state variables

Variable	Theory	Empirical evidence
Short rate	● Reflects expected inflation, related to business cycle ● Flight to quality reduces short rates	● Fama and Schwert (1977) ● Fama and Gibbons (1984) ● Longstaff (2004)
Term spread	● Reflects expectations on future interest rates and economic activity ● Reflects compensation for exposure to discount rate shocks for all long-term securities	● Campbell (1987) ● Fama and French (1989) ● Ang, Piazessi and Wang (2006) ● Estrella and Trubin (2006)
Default spread	● Increasing spread adversely affects economic activity ● Signals rising risk aversion	● Keim and Stambaugh (1986) ● Fama and French (1989) ● Duffie and Berndt (2011) ● Faust el al (2013)
Dividend yield	● Higher required return increases the yield	● Campbell and Shiller (1988) ● Fama and Gibbons (1988, 1989)

2 Campbell and Cochrane (1999) and Constantinides and Duffie (1996).

3 For similar results regarding the link between fast-moving variables and future economic conditions, see Fama (1981) or Aylward and Glen (1995).

and economic outlook. The empirical literature cited in figure 2 also documents the relationship of those variables for expectations about aggregate bond and stock returns, as well as economic activity.

Defining regimes: 'good' and 'bad' times

The variables that seem to be relevant for describing the state of the economy could be used in different ways. For the investor who is highly exposed to corporate bonds, cyclicality related to the credit spread might be the most relevant. Pension funds with long-term liabilities may care more about the term structure of interest rates. The analysis below does not focus on specific investors' needs, but rather tries to capture the aggregate conditions of the economy. We combine all the state variables from the previous section to form the two composite indicators of 'good' and 'bad' times. Relying on a single variable might be misleading in defining aggregate conditions, since some of the information that is captured by one variable may not be captured by others. Relying on multiple variables will lead to more robust classification of states. Of course, our approach is just one of the many possible ways of forming the composite indicator. Our framework is sufficiently flexible, however to accommodate dimensions other than risk-tolerance and economic outlook, such as liquidity and uncertainty for example.

Thus, we draw on two indicators of aggregate conditions that reflect investors' risk tolerance and macroeconomic outlook. These quantities are unobservable expectations but can be linked to observed variables. We follow a standard methodology to combine macroeconomic variables into composite indicators.

At each point in time, we define risk tolerance based on the econometric expectation of the market premium (stock market excess return) where a high equity premium translates into low risk tolerance. Following Petkova and Zhang (2005), we use the short-term interest rate, term spread, default spread and dividend yield to capture risk tolerance.[4] We use the same four variables to form the expectations regarding the macroeconomic activity, proxied by industrial production growth (as in Boons [2016]).[5] Figure 3 reports loadings for the aggregate indicators on state variables.[6]

The economic outlook is positive when the level and slope of the yield curve is high. The default spread has a strong negative impact on the economic outlook. Furthermore, we can see that risk-tolerance is high when investors demand lower dividend yields. Overall, loadings on state variables reflect economic theory.

The two composite indicators try to capture different dimensions of risk, which is why they load differently on state variables. We combine both indicators to reduce the risk of misspecification of economic conditions, and obtain a more reliable regime classification. The economic state will be classified as 'bad times' (respectively 'good times') only if both composite measures indicate the same. Using this procedure, we define four regimes (see figure 4).

The high/low regimes are based on the long-term median values of each indicator. Going forward, we will refer to the regimes with high (low) risk tolerance and positive (negative) economic outlook as 'good times' (respectively, 'bad times'). We will not distinguish between two mixed regimes, but we will report results for both.

As expected, there is good agreement between the composite indicators. However, the two sometimes disagree as well. For example, there are 37 months when the risk-tolerance was in the top quartile and the economic outlook was in the bottom quartile (bottom left corner of figure 5). This is why we think that combining different composite measures will yield the more reliable regime classification. Nevertheless, the extremely bad states are signalled by both indicators simultaneously (the first quartiles, in the top left corner).

Description of the data

Our analysis concerns six equity factors that have been well documented in the academic literature. These are the size, value, momentum, low risk, high profitability and low investment factors in the US. The monthly returns are available since July 1963, which gives us almost 54 years (or 642 months) to analyse.[7]

We use secondary market rate on three-month Treasury bills for the short-term interest rates, 10-year minus one-year Treasury constant maturity rate for the term spread, Baa minus Aaa corporate bond yield for the default spread, 12-month trailing dividend yield on CRSP value-weighted index, and seasonally-adjusted industrial production index for the macroeconomic activity.[8]

Conditionality of factor returns

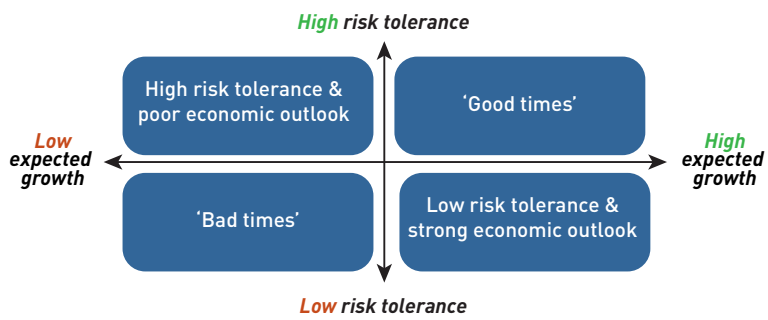
We now move to measuring the state-dependency of factor premia. Figure 6 shows conditional annualised returns in different macro regimes. Our main focus is the difference between 'good' and 'bad' times, which we refer to as regime spread. We also indicate statistical significance at different confidence levels.

3. Loadings on state variables for composite indicators

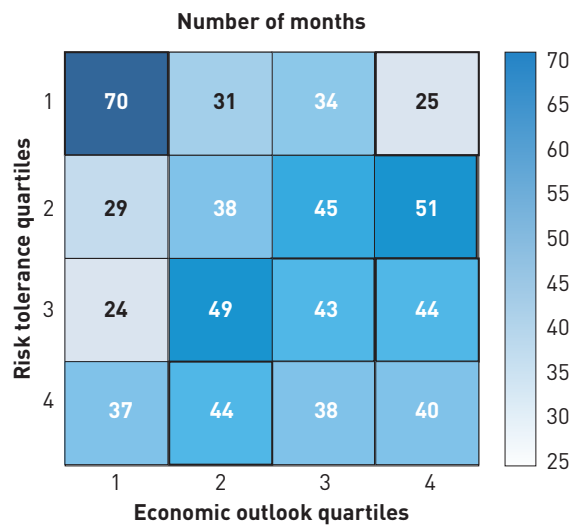
US June 1963–December 2016	Loadings on state variables for	
	Economic outlook	Risk tolerance
Yield on T-bills	**0.24** †	**0.20** †
Term spread	**0.29** ‡	−0.01
Default spread	**−0.39** ‡	0.00
Dividend yield	−0.02	**−0.20** ‡

The table reports coefficients from the regressions, where the independent variables are yield on T-bills, term spread, default spread and dividend yield, and the dependent variables are equity market excess returns and growth in industrial production over the next month. The economic outlook is the expected growth rate in industrial production. The risk-tolerance is the expected market excess return with negative sign (thus, coefficients also have negative sign). Statistically significant numbers at 10%, 5% and 1% are indicated by *, †, and ‡ respectively. We use Newey-West standard errors with number of lags equal to six.

4. Defining macroeconomic regimes



5. Monthly distribution of sample into different quartiles of risk tolerance and economic outlook



4 The risk-tolerance at month *t* is the expected market excess returns over the month from *t* to *t+1*: $E[R]_{t+1|t} = \delta_0 + \delta_1 TB_t + \delta_2 TERM_t + \delta_3 DEF_t + \delta_4 DIV_t$. The coefficients for state variables are estimated using the following regression: $R_{t+1} = \delta_0 + \delta_1 TB_t + \delta_2 TERM_t + \delta_3 DEF_t + \delta_4 DIV_t + \varepsilon_t$

5 Our ultimate goal is not to predict the market or the economy. The variance of dependent variables explained in the regressions is too small to provide such abilities. Rather, we are interested in summarising information in a set of macro variables so as to be able to interpret them as an econometric expectation of overall macro conditions

6 The independent variables are scaled to have zero mean and variance equal to that of dependent variable. The magnitude of the loadings will therefore be comparable.

7 The data for monthly factor returns, including market excess returns, come from K. French library and AQR database (only for the low risk factor).

8 The corporate yields are based on Moody's seasoned Baa and Aaa bonds. The data for bond yields and seasonally adjusted industrial production index was retrieved from the Federal Reserve Bank of St Louis. Using Chicago FED National Activity Index (CFNAI) or GDP instead of industrial production index yields similar results.

6. Conditional performance of factor returns

US July 1963–December 2016	Size	Value	Momentum	Low risk	High profitability	Low investment
Panel A: Unconditional annualised average returns (%)						
Full sample	2.6†	4.0‡	7.1‡	9.3‡	2.7‡	3.5‡
Panel B: Conditional annualised average returns (%)						
Good times	−4.2	6.9‡	16.0‡	7.7‡	5.1†	4.6†
High risk tolerance/Low exp. growth	2.3	6.0†	9.5†	11.1‡	2.5	5.3†
Low risk tolerance/High exp. growth	5.3†	4.9‡	7.7‡	12.8‡	1.5	3.0†
Bad times	7.7‡	−1.2	−3.7	6.1‡	1.5	1.2
Regime spread	**11.8‡**	**−8.1†**	**−19.7‡**	−1.6	−3.6	−3.4

The analysis is based on monthly returns from 30 June 1963 to 31 December 2016. The reported figures are annualised average (geometric) returns of long/short factors within each macroeconomic regime. Statistically significant numbers at 10%, 5% and 1% are indicated by *, †, and ‡ respectively. Bold type indicates monotonic increase/decrease in returns from good state to bad state. Monotonicity is indicated by bold type. While assessing monotonicity, we require values for all the regimes (excluding extreme ones) to be between 'good' and 'bad' times.

7. Conditionality of market exposures

US July 1963–December 2016	Size	Value	Momentum	Low risk	High profitability	Low investment
Panel A: Unconditional annualised average returns (%)						
Full sample	0.19‡	−0.17‡	−0.13‡	−0.06†	−0.12‡	−0.17‡
Panel B: Conditional annualised average returns (%)						
Good times	0.20‡	−0.28‡	0.03	−0.10	−0.18‡	−0.28‡
High risk tolerance/Low exp. growth	0.20‡	−0.33‡	0.00	−0.18‡	−0.18‡	−0.22‡
Low risk tolerance/High exp. growth	0.20‡	−0.11†	0.13*	−0.02	0.01	−0.10‡
Bad times	0.15‡	0.02	−0.40‡	0.03	−0.09‡	−0.10‡
Regime spread	−0.05	0.30‡	−0.43‡	0.12	0.09*	0.18‡

The analysis is based on monthly returns from 30 June 1963 to 31 December 2016. The reported figures are regression coefficients from a one-factor model where the dependent variable is factor returns and the independent variable is market excess return (CAPM model). Regressions are run using calendar months (pooled together) that constitute each macroeconomic regime. Statistically significant numbers at 10%, 5% and 1% are indicated by *, †, and ‡ respectively. Bold type indicates monotonic increase/decrease in returns from good state to bad state. Monotonicity is indicated by bold type. While assessing monotonicity, we require values for all the regimes (excluding extreme ones) to be between 'good' and 'bad' times.

8. Decorrelation ≠ regime independence – example of equally weighted value and momentum

US July 1963–December 2016	Average volatility of factors	Volatility	Reduction in volatility	Average regime dependence	Regime dependence	Reduction in regime dependence
Allocating to factors with similar conditionality						
Momentum and value (EW)	2.2%	8.0%	−34.3%	5.1%	5.0%	−2.7%
Allocating to factors with opposite conditionality						
Momentum and size (EW)	12.6%	8.9%	−29.3%	5.8%	1.7%	−70.8%

The table reports annualised volatility, the weighted-average volatility of ingredients, the reduction in volatility due to the interaction effect, regime dependency, the weighted-average regime dependency of ingredients and the reduction in regime dependency. The regime dependency is computed as a root mean squared error of conditional annualised returns across regimes.

We can see that the regime spread for three factors out of six reveals significant dependency on macro regimes. The size factor performed better during the 'bad times', while the value and momentum factors preferred 'good times'. This suggests that adding size to the multi-factor portfolio will reduce state-dependency, given that it is the only factor with the opposite behaviour across different states. It is worth mentioning that value and momentum have similar conditionality. This seems to be counter to some conventional wisdom because the two factors are widely reported to have negative correlation. However, it is well known that strategies with low correlation on average may still lead to simultaneous losses when bad economic regimes hit. Our finding suggest that value and momentum, despite their low correlation, are not good candidates to achieve good diversification across macroeconomic regimes.

Conditionality of market exposures

Factor returns used in the analysis are dollar-neutral portfolios that do not explicitly control for the market exposure (except for the low risk factor, which is market-neutral ex-ante by construction). However, there is ample evidence suggesting that the market exposure of equity factors undergoes substantial variation over time, which could be driven by business cycle fluctuations (see Amenc, Goltz and Lodh [2018] for a more detailed discussion). Analysing implicit risks such as time-varying market exposure can bring important insights for improving risk management. For example, one would prefer to avoid increases in market exposure when the risk tolerance is low. We thus assess how the market exposure of factors changes across macroeconomic regimes.

Results in figure 7 suggest that the market exposure of the size factor is positive and stable across states. Value experiences increases in market beta during the 'bad times'. This is in line with the theory of costly reversibility, which causes assets in place to be harder to reduce, leading to increased market risk for value stocks compared to growth stocks. Petkova and Zhang (2005) report similar results. The momentum factor has opposite cyclicality in terms of market exposures. Such behaviour is natural for the momentum strategy since the past winners are likely to be low beta stocks in bad times. While value and momentum premia are expected to suffer both at the same time, they will provide more stable market exposure if combined. The variation is less pronounced for investment and profitability, and insignificant for the low risk factor. Overall, we can conclude that market beta variation of premia is in line with the factors' economic mechanisms.[9]

Implications for factor investors

The existing analysis provides some interesting insights that may have implications for factor investors. Below, we illustrate how information on the sensitivity to macroeconomic regimes may influence factor allocation decisions. Of course, practical implementations of such approaches may need to consider additional issues not treated here, where we focus on allocations across long/short factors without considering implementation issues such as liquidity and transaction costs, for example.

Decorrelation does not guarantee diversification across regimes

The standard idea of diversification comes with the concept of decorrelation, which means that combining two assets that are not perfectly correlated will lead to a reduction in risk (volatility). However, exploiting imperfect correlations across returns will not necessarily result in balanced performance across macro regimes.

As a simple case, consider a portfolio that has equal exposure to factors such as value and momentum. The negative correlation between the two leads to reduction in volatility by 34% compared to the average volatility of the two factors. Nevertheless, there is no impact on the regime dependency, measured as a root mean squared deviation of conditional returns across macro regimes. Regime dependency of the portfolio is almost identical to that of holding each asset in isolation. A similar level of volatility reduction (29%) is observed if the size and momentum factors are combined. However, since they have opposite macro-sensitivity, the regime dependency of the portfolio is only 1.7% compared to 5.8% for its components, as shown in figure 8. This is equivalent to roughly 70% reduction in average regime dependency, compared to only 3% for value and momentum. This illustration shows that combining factors with offsetting macro cyclicality (such as momentum and size) leads to a significant reduction in regime dependency, while combining factors with similar macro cyclicality (such as momentum and value) does not help improve diversification across regimes.

Designing a regime-aware allocation

Intuitively, adding more factors into a portfolio will reduce the cyclicality. However, selecting factors carefully is still important if one aims to diversify regime-dependency. Figure 9 shows that the returns of a five-factor allocation that excludes the size factor still reveal pro-cyclical behaviour. The conditional returns in 'bad times' are much lower than in 'good times'. If we add the size factor, we see a reduction in the dependency on macroeconomic regimes. The returns for the six-factor allocation strategy show less difference across good times and bad times. However, there is still pronounced asymmetry in conditional performance, resulting in a 4% return difference between good and bad times.

To further reduce the cyclicality of a multi-factor portfolio, we assess a minimum regime-dependent allocation, which we refer to as MRD. This allocation exploits information on macro cyclicality to come up with a macro-neutral allocation. The following optimisation procedure will minimise regime-dependency, subject to constraints:

$$w* = \arg\min \left\{ \sum_{i=1}^{N} \left(w^T x_i - w^T x_0 \right)^2 \right\}$$

where x_i is the vector of conditional mean returns (of each factor) in regime *si*, N is the number of regimes and x_0 is the target with respect to which we want to minimise deviation. In our case, the target will be the vector of

9 Note that the state-dependency of market exposures cannot fully explain the cyclicality of factor returns. After adjusting for the market, the size, value and momentum factors still show high dependency on macro regimes, with regime spreads of 8.2%, −8.1% and −11.1% respectively.

9. Regime dependency of different multi-factor allocations

US July 1963–December 2016	Annualised returns in 'good' times	Annualised returns in 'bad' times	Regime spread	Regime dependency
Case 1: Naive diversification across pro-cyclical factors				
EW 5F (ex-size)	8.4%‡	1.2%	–7.2‡	2.7%
Case 2: Naive diversification – including counter-cyclical size				
EW 6F	6.3%‡	2.4%†	–4.0†	1.7%
Case 3: Minimum regime-dependent allocation				
MRD	3.4%‡	3.1%‡	–0.3%	0.5%

Allocation weights	Size	Value	Momentum	Low risk	High profitability	Low investment
MRD	28.0	10.7	3.6	3.1	33.9	20.6

The table reports annualised average returns in 'good' and 'bad' states, difference between the two – regime spread and regime dependency – computed as a root mean squared error of conditional returns across regimes. Statistically significance of returns at 10%, 5% and 1% are indicated by *, †, and ‡ respectively. The bottom part reports allocation weights to each factor for minimum regime dependency approach. The MRD is restricted to allocate effectively in four factors at least (ie, effective number of factors is at least four, where the effective number is computed as an inverse of the sum of squared weights).

unconditional average factor returns. The objective function will thus minimise the sum of squared deviations of conditional returns from unconditional returns.

Note that this framework allows the incorporation of multiple regime classifications, as well as specific investor views of that may differ from our base case. Moreover, the use of conditional returns is not a requirement since vector x can easily be replaced by different measures of sensitivity, such as betas.

We test whether the MRD approach can achieve close to zero regime dependency without concentrating in few factors. We also require factor weights to be non-negative:

$$w \geq 0; \quad \left(w^T w\right)^{-1} \geq 4; \quad w^T e = 1$$

where e is a column vector of ones. The results in figure 9 suggest that regime dependency can be reduced to 0.5% when effectively invested in at least four factors. Conditional returns across states is almost identical and statistically significant at the 1% level. Factor weights also reflect our previous findings. More specifically, the MRD allocation favours the size factor because of its offsetting macro-exposure relative to others. The 'quality'-related factors such as profitability and investment also received higher weights due to their weak dependency on macro regimes. On the contrary, two factors with the most pronounced pro-cyclical behaviour, value and momentum, were given less weight compared to the equal-weighting approach.

Conclusion

Our analysis suggests that the value and momentum factors behaved in a cyclical manner, performing poorly in 'bad' economic states, when the risk-tolerance was low, and the economic outlook was weak. We also find that the size factor has an important role in a multi-factor setting, since it reveals opposite macro sensitivity relative to value and momentum. The cyclicality for the investment and profitability factors is less pronounced, suggesting a role for the two factors in multi-factor allocation. Even though the regime dependency among factors is not identical, naïve diversification across different factors does not fully diversify business cycle risks. An explicit minimum regime dependency objective allows diversification to be further improved across regimes.

There are obvious questions that our analysis does not address. In particular, we use a particular definition of economic states. However, our composite measure of good and bad times is just one possible way of defining composite regimes. The fast-moving macro variables we employ could easily be used to derive different regime definitions. Moreover, our framework is flexible enough to be augmented with multiple regime classifications. This would allow the risk of regime misspecification to be reduced. Based on the empirical evidence in the asset-pricing literature, liquidity and uncertainty regimes would be good candidates as additional dimensions in our analysis. Moreover, particular investors could have a concern to manage their macroeconomic sensitivities with respect to a particular state variable such as the short rate or the credit spread, rather than with respect to a composite regime describing the overall macroeconomic state. Again, our framework can accommodate such investor objectives concerning particular macro state variables.

Whatever the objective of an investor, that equity factors introduce some dependencies on macroeconomic regimes has been well documented both empirically and theoretically. Thus investors with exposure to value, momentum, and other factors, need to consider these dependencies more closely if they want to understand the risks they are exposed to.

References

Amenc, N., F. Goltz and A. Lodh (2018). Mind the Gap: On the Importance of Understanding and Controlling Market Risk in Smart Beta Strategies. *Journal of Portfolio Management* 44(4): 60–70.

Ang, A. (2014). *Asset Management: A Systematic Approach to Factor Investing*. New York: Oxford University Press.

Ang A., M. Piazessi and M. Wei (2006). What does yield curve tell us about GDP growth? *Journal of Econometrics* 131: 359–403.

Asness, C. (1992). Changing Equity Risk Premia and Changing Betas over the Business Cycle. University of Chicago Working Paper. January

Aylward, T., and J. Glen (1995). Some international evidence on stock prices as leading indicators of economic activity. Unpublished working paper, IFC.

Boons, M. (2016). State variables, macroeconomic activity, and the cross section of individual stocks. *Journal of Financial Economics* 119: 489–511.

Campbell, J.Y. (1987). Stock returns and the term structure. *Journal of Financial Economics* 18: 373–399.

Campbell, J.Y., and J.H. Cochrane (1999). By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior. *Journal of Political Economy* 107(2): 205–251.

Campbell, J.Y., and R.J. Shiller (1988). Stock Prices, Earnings, and Expected Dividends. *Journal of Finance* 43(3): 661-676.

Cederburg, S., and M.S. O'Doherty (2016). Does It Pay to Bet Against Beta? On the Conditional Performance of Beta Anomaly. *Journal of Finance* 71(2): 737–774.

Cochrane, J.H. (2008). The Dog That Did Not Bark: A Defense of Return Predictability. *The Review of Financial Studies* 21(4): 1533–1575.

Constantinides, G. M., and D. Duffie (1996). Asset Pricing with Heterogeneous Consumers. *Journal of Political Economy* 104(2): 219–240.

Devarajan, M., V. Naik, A. Nowobilski, S. Page and N. Pedersen (2016). *Factor Investing and Asset Allocation – A Business Cycle Perspective*. The CFA Institute Research Foundation.

Duffie, D., and A. Berndt (2011). Explaining corporate debt returns. Working Paper, Stanford University.

Estrella A., and M. Trubin (2006). The yield curve as a leading indicator: some practical issues. *Economics and Finance*, Federal Reserve Bank of New York 12(5).

Fama, E.F. (1981). Stock Returns, Real Activity, Inflation, and Money. *The American Economic Review* 71(4): 545–565.

Fama, E.F., and K.R. French (1988). Dividend yields and expected stock returns. *Journal of Financial Economics* 22: 3–25.

Fama, E.F., and K.R. French (1989). Business conditions and expected returns on stocks and bonds. *Journal of Financial Economics* 25: 23–49.

Fama E.F., and M.R. Gibbons (1984). A comparison of inflation forecast. *Journal of Monetary Economics* 13(3): 327-348.

Fama, E.F., and G.W. Schwert (1977). Asset returns and inflation. *Journal of Financial Economics* 5: 115–146.

Faust, J., S. Gilchrist, J.H. Wright and E. Zakrajssek (2013). Credit Spreads as Predictors of Real-Time Economic Activity: A Bayesian Model-Averaging Approach. *Review of Economics and Statistics* 95(5): 1501-1519.

Gordon, Myron J. (1959). Dividends, Earnings and Stock Prices. *Review of Economics and Statistics* 41(2): 99–105.

Gupta, A., A. Kassam, R. Suryanarayanan and K. Varga (2014). Index Performance in Changing Economic Environments. MSCI Research Insights.

Harvey, C. R. (1989). Time-Varying Conditional Covariances in Tests of Asset Pricing Models. *Journal of Financial Economics* 24: 289–317.

Ilmanen, A., T. Maloney and A. Ross (2014). Exploring Macroeconomic Sensitivities: How Investments Respond to Different Economic Environments. *Journal of Portfolio Management* 40(3).

Keim, D.B., and R.F. Stambaugh (1986). Predicting returns in the stock and bond markets. *Journal of Financial Economics* 17: 357–390.

Liew, J., and M. Vassalou (2000). Can book-to-market, size and momentum be risk factors that predict economic growth? *Journal of Financial Economics* 57: 221–245.

Liu. X., and L. Zhang (2008). Momentum Profits, Factor Pricing, and Macroeconomic Risk. *Review of Financial Studies* 21(6): 2417–2448.

Longstaff, F.A. (2004). The Flight-To-Quality Premium in U.S. Treasury Bond Prices. *Journal of Business* 77(3): 511–526.

Merton, R.C. (1973). An intertemporal capital asset pricing model. *Econometrica* 41: 867–887.

Petkova, R. (2006). Do the Fama-French Factors Proxy for Innovations in Predictive Variables? *Journal of Finance* 61(2): 581–612.

Petkova R., and L. Zhang (2005). Is value riskier than growth? *Journal of Financial Economics* 78: 187–202.

Roll, R. (1977). A critique of the asset pricing theory's tests, part I: on past and potential testability of the theory. *Journal of Financial Economics* 4: 129:176.

Ross, S. A. (1995). *Neoclassical Finance*. Princeton University Press, Princeton, NJ, p. 64.

Stock, J.H., and M.W. Watson (1999). Business cycle fluctuations in U.S. macroeconomic time series. In: Taylor, J.B., and M. Woodford (Eds), *Handbook of Macroeconomics* 1: 3–64.

Ung, D., and P. Luk (2016). What Is in Your Smart Beta Portfolio? A fundamental and Macroeconomic Analysis. *Journal of Index Investing* 1: 49-77.

Vassalou, M., and Y, Xing (2004). Default Risk in Equity Returns. *Journal of Finance* 59(2): 831–868

Factor investing from a total portfolio construction perspective

Kevin Zhu, Managing Director, Head of Portfolio Construction, OPTrust; **Michael Bonazza**, Senior Portfolio Manager, Portfolio Construction, OPTrust; **Matthew Zhao**, Portfolio Manager, Portfolio Construction, OPTrust

Investment framework and approach

At OPTrust, our mission is "paying pensions today, preserving pensions for tomorrow". Our core principle is to align the interests of our investment teams with those of our members. This means keeping the Plan in balance to preserve its fully-funded status, by ensuring contributions and investment returns are sufficient to fund the benefits we have promised (figure 1). We call this approach member-driven investing (MDI). From an investment standpoint, we need to take enough risk to earn the returns we need to keep the Plan sustainable over the long term, but not so much risk that we jeopardise the stability of contribution rates and benefit levels. Our investment strategy is designed to strike the right balance between these two objectives underpinning OPTrust's MDI strategy:

- ***Sustainability*** – generating sufficient returns to keep the Plan fully funded; and,
- ***Stability*** – keeping contributions and benefits at their current levels and as stable as possible throughout time.

We achieve this balance by adopting a total fund mindset and an approach that allocates risk across asset classes and strategies in a diversified and risk-efficient manner.

OPTrust's portfolio construction approach has evolved substantially over the last three years since the inception of our MDI strategy. We have moved from a traditional asset-based approach to a risk factor-based approach to construct our total fund portfolio. This shift recognises that the behaviour of different asset classes is driven by a common set of risk factors such as growth, inflation and real interest rates. Moreover, the benefits we have promised our members – ie, our liabilities – are also impacted by these risk factors.

A pension portfolio that is diversified only in asset space may be exposed to concentrated risk exposures. This portfolio may suffer larger than expected drawdowns, and ultimately, have a lower chance of meeting its liabilities. This is why we take a risk factor-based approach – it allows us to 'look through' our assets and construct a portfolio that is truly diversified across the major risk factors, leading to higher risk-adjusted returns and a lower risk of being underfunded. Our goal is to construct the portfolio with a balanced risk factor exposure to achieve enough return to keep the Plan fully funded, at the lowest level of risk (figure 2).

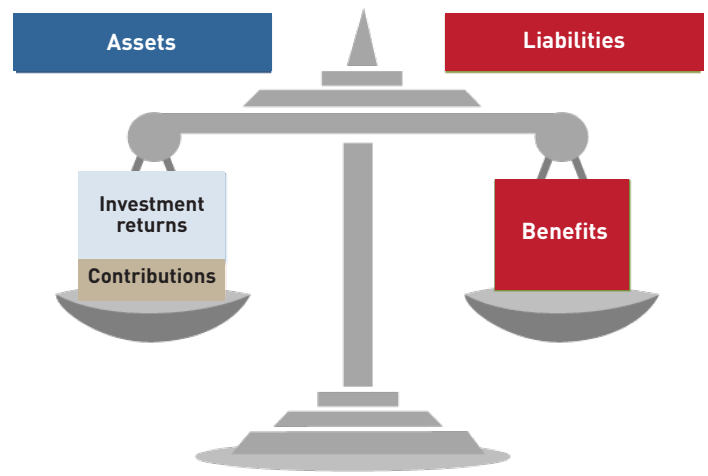
The identification and mapping of asset classes and strategies to risk factors is a critical step in the process. We consider a broad universe of risk factors in our portfolio design, including macro risk factors (eg, economic growth, real interest rate, inflation, etc) and style risk factors (eg, value, momentum, carry, volatility – figure 3).

OPTrust's experience in factor investing

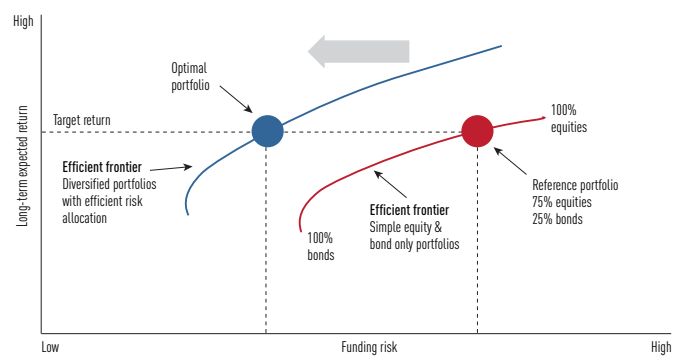
The first step in our process is to understand the key investment characteristics of different risk factors, for example: their risk and return profiles; sensitivity to different economic regimes and market environments; and their interactions with each other. Understanding how each factor behaves helps us to choose the right mix of factors as we allocate risk across our portfolio.

Historically, we observe that macro factors tend to exhibit regime-dependent behaviours – as would be expected – while style factors within asset classes are more regime-agnostic. Furthermore, factors tend to diversify the risk from each other, and some of the diversifying features are also regime-dependent. For example, equity and rate factors are uncorrelated on average, but their correlation turns negative in a recessionary economic environment. Interestingly, most style factors tend to exhibit low correlations with macro

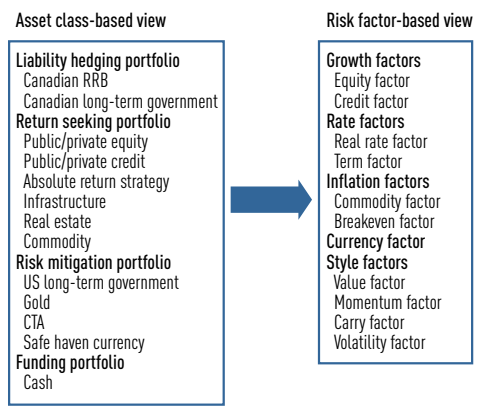
1. Member-driven investing seeks to keep the Plan in balance



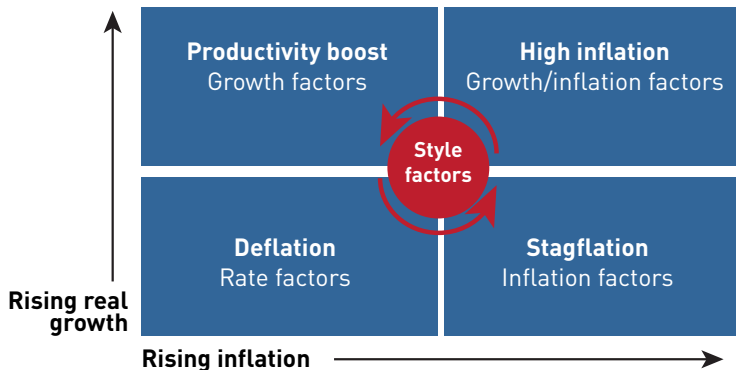
2. Our investment goal is to earn our target return at the lowest level of funding risk



3. Transformation of OPTrust's portfolio construction approach

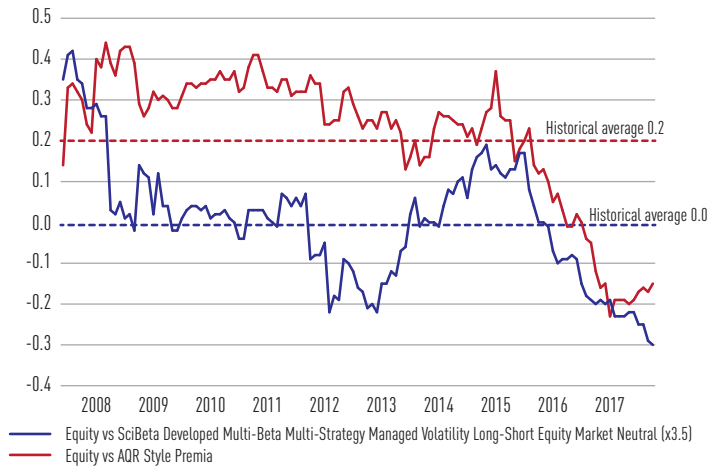


4. Factor performance in different economic regimes



Note 1. Growth factors: equity, credit; rate factors: real rate, term spread; inflation factors: commodities, breakeven; style factors: value, momentum, quality, size, volatility.
Note 2. Based on historical stylised facts.

5. Low correlation between style factors and equity factors



Note 1. SciBeta Developed Multi-Beta Multi-Strategy Managed Volatility Long/Short Equity Market Neutral (x3.5) strategy consists of equity only.
Note 2. AQR Style Premia strategy consists of equity, fixed income, commodities and currencies.

factors regardless of the economic regime, making them an appealing source of risk premia from a portfolio diversification standpoint.

These findings are important to our portfolio construction process. We use, among other tools, an economic quadrant framework to help us build our portfolio. Our goal is to have an 'all-weather' type of portfolio with more balanced factor exposures across environments. Figure 4 provides a conceptual illustration of our economic quadrant framework, defined by growth on the y-axis and inflation on the x-axis, with outperforming factors identified within each of the four quadrants. Once we better understand factor characteristics, we can then decide how best to allocate our risk to achieve better portfolio balance across growth/inflation regimes.

Given that macro factor investing is more straightforward and well established, we want to share our thoughts and experience on investing in alternative (non-macro) factors, namely style factors. We will explain their roles in our portfolio and how we invest in them.

Our beliefs on style factors

OPTrust believes style factor premia exist and can be harvested owing to both structural market inefficiencies and established investor behaviours. Beyond positive long-term expected returns, style factors are found to have low correlations with macro factors (see figure 5) and their investment characteristics are less economic regime-dependent. Therefore, adding those exposures to our total portfolio helps improve performance on a risk-adjusted basis.

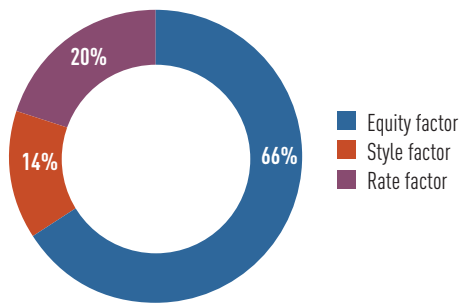
Style factors are not new to institutional investors and many already have these exposures embedded in their portfolios. For example, a long-only equity manager may pursue active strategies with quality factor tilts, while a private equity manager may favour a value factor in its portfolio design. However, style factor exposures have mostly been accessed at a small scale, with macro factors the overwhelming drivers of portfolio performance. Resistance to change, and inflexible governance and incentive frameworks, partly explain this apparent imbalance in factor exposures. Many pension funds operate under a benchmark-driven incentive framework in which a portfolio manager is constrained by a risk budget and, therefore, has little incentive or ability to pursue significant style factor exposures that could generate large tracking errors. More sophisticated investors have explored style factor exposures via long/short strategies; however, they are largely housed in 'alpha' portfolios with small risk budgets.

Because of these constraints, most investors have yet to extract meaningful contributions to overall portfolio performance from style factors. Figure 6 shows the marginal risk contribution of style factor exposures in a traditional 60/40 US equity/bond portfolio with equity being invested in the Scientific Beta Developed High-Factor-Exposure Multi-Beta Multi-Strategy 6-Factor Equal Weight strategy. As shown, style factor exposure embedded in this long-only equity smart beta strategy does not make a meaningful contribution to the total portfolio risk, as the equity factor remains the dominant risk driver in the long-only smart beta strategy.

How OPTrust invests in style factors

At OPTrust, our success measure is the funded status, as opposed to our return versus a benchmark/policy portfolio. At the portfolio manager level, we have been moving away from arbitrary benchmarks, and towards customised benchmark designs to incentivise investment teams to deliver the desired

6. Risk contribution of factor exposures to 60/40 equity/bond portfolio



Note. Style factor exposure is estimated by taking the cap-weighted equity beta exposure out of the SciBeta Developed High-Factor-Exposure Multi-Beta Multi-Strategy Six-Factor Equal-Weighted strategy

factor exposures to the total fund. By doing so, we have removed barriers that have traditionally prevented investors from pursuing certain factor exposures (eg, style factors) at scale.

From an implementation standpoint, we currently access style factors in two ways:

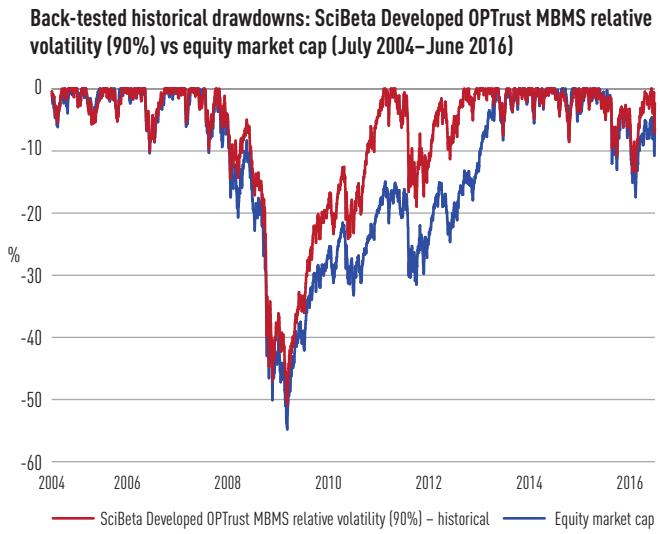
- Long-only: smart beta strategy in the long-only equity portfolio; and
- Long/short: multi-asset/multi-style factor premia strategy in the absolute return portfolio.

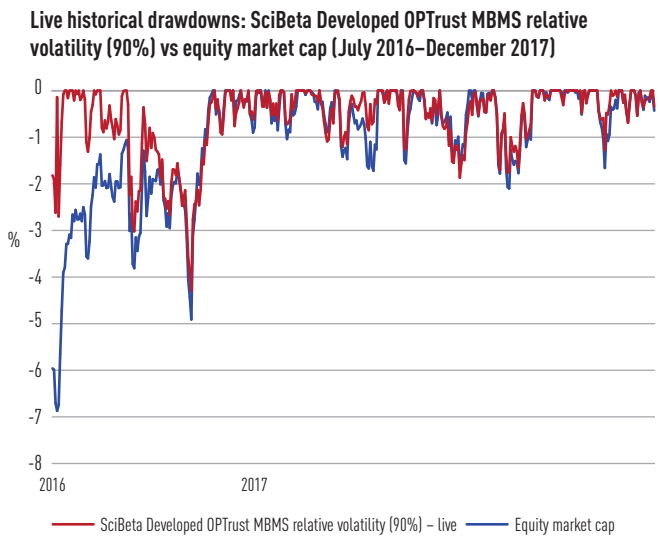
For the long-only equity smart beta strategy, the portfolio is mandated to generate more risk-efficient (ie, higher Sharpe ratio) equity exposure with lower risk than the passive market cap index. The way we gain style factor exposures in this long-only mandate is not very different from others who either invest in long-only active equity strategies or smart beta equity exchange-traded funds (ETFs). More importantly, we fully recognise that the contribution of style factor exposures in this portfolio to the total fund remains small due to the dominance of the equity factor risk contribution.

Having said that, what differentiates us from others is that we do not constrain style factor exposures in the construction of this portfolio – for example, by constraining active risk to an industry benchmark. We instead focus on the key investment characteristics, such as volatility and Sharpe ratio. This provides more flexibility in portfolio construction to index providers and/or managers to deliver the most efficient solution to achieve our objectives.

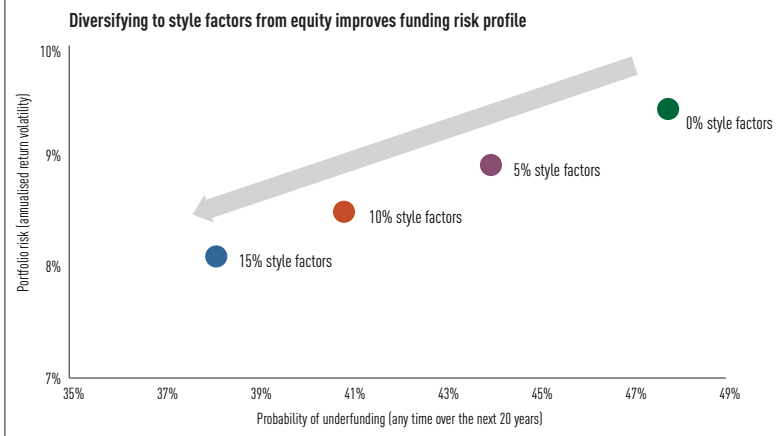
OPTrust is currently investing in the Scientific Beta long-only equity smart beta strategy with the objectives of achieving at least the same return as the MSCI World (market cap) equity index and 10% volatility reduction relative to the market cap equity index. The style factor exposures in this portfolio are the outputs instead of the inputs to portfolio construction. Since inception of our investment in this strategy, the portfolio has delivered the expected outcome. Moreover, this portfolio has exhibited a better drawdown profile than the market cap index on average, which is a key

7. Historical and live drawdown profile of OPTrust invested Scientific Beta smart beta equity strategy





8. Impacts of increasing style factor exposures on OPTrust's portfolio



Note 1. The OPTrust management funding ratio was 111% as of December 2017.
Note 2. Results based on OPTrust ALM simulation analysis.
Note 3. OPTrust style factors are represented by alternative risk premia, where changes to the style allocation are fully offset by the equity allocation.

metric for OPTrust given our objective of maintaining a stable funded status (figure 7).

While smart beta strategies allow us to access style factors, we cannot add meaningfully to this exposure without taking additional macro factor risk. To further scale up our style factor exposure, we invest directly via long/short strategies, and we do so across asset classes in the alternative risk premia (ARP) space.

When investing in long/short style factor strategies, we pay a lot of attention to capital efficiency; that is, the amount of capital we need to commit to get the risk/return characteristics we are looking for. Since capital is a scarce resource, our goal is to extract as much exposure as possible with the lowest capital usage. This means that we require a certain minimum level of risk for those strategies such that they can deliver the required performance objectives in sufficient scale. We have been working extensively with our partners to tailor strategy solutions to meet our specific needs. For instance, if we have the choice between two solutions with equivalent risk-adjusted returns and correlation features, we will choose the strategy that runs at a higher level of risk. This approach enables us to be more capital efficient, in turn broadening the quantity of risk premia we can access across the portfolio.

Given our investment objective to develop a more risk balanced total portfolio, we currently target a capital allocation of 10–15% to pure style factor exposures in our long-term strategic portfolio. Our asset-liability study suggests that, with this magnitude of style factor exposures, we can achieve a meaningful improvement in our funding ratio stability – ie, reducing the likelihood of being underfunded (figure 8).

Conclusions

Our mission at OPTrust is "paying pensions today, preserving pensions for tomorrow". Delivering on our mission means earning enough return to ensure the Plan is sustainable over the long term, at the lowest level of risk. Constructing a portfolio that is resilient across different economic and market environments gives us the best chance of delivering on this objective. We believe that this is best accomplished by viewing our exposures through a risk factor lens; specifically, by building a portfolio with balanced exposures across different risk factors, including macro and style factors. Constructing the portfolio in this way has reduced our dependence on common risk drivers, such as equity risk, to earn the returns we need to keep our Plan sustainable, while improving its risk-adjusted return.

Accessing the benefits of style factors in scale requires the right incentive structure: one that is focused on the investment characteristics of the strategy/portfolio in absolute terms, instead of versus arbitrary return benchmarks. At OPTrust, we are focused on what our members care about – the funded status of the Plan – and believe that accessing style factors directly, in size, combined with balanced macro risk factor exposure, gives us the best chance of delivering on our mission.

Exposed to nonsense?

Spurious factors in popular investment tools

Felix Goltz, Head of Applied Research, EDHEC-Risk Institute, Research Director, ERI Scientific Beta; **Ben Luyten**, Quantitative Research Analyst, ERI Scientific Beta

Analytic tools do not employ academically-grounded factors and their factor-finding process maximises the risk of ending up with false factors.

Thus, most factors used in commercially available analytic tools are likely false.

Non-standard factors lead to mismeasurement of exposures and may capture exposure to redundant factors.

Analytic tools for investors distort the key idea of factor investing because they lack transparency and expose investors to providers' conflicts of interest.

The promise of factor investing

Factor investing offers a big promise. By identifying the persistent drivers of long-term returns in their portfolios, investors can understand which risks they are exposed to, and make explicit choices about these exposures. This idea has gained popularity among long-term investors ever since the publication in 2009 of an influential report by finance professors on the performance of the Norwegian sovereign fund.[1]

An often-cited analogy is to see factors as the 'nutrients' of investing. Just as information on the nutrients in food products is relevant to consumers, information on the factor exposures of investment products is relevant to investors. This analogy also suggests that factors cannot be arbitrary constructs. What would you think if Nestlé used its own definition of 'saturated fat' for the information on its chocolate packets and if McDonald's also had its own, but different, definition for the content of its burgers? Further, would it not be curious if both definitions had nothing to do with the definition that nutritionists and medical researchers use?

When it comes to information about factors, however, this is exactly the situation that we find. There is a host of providers offering analytic toolkits to identify factor exposures of an investor's portfolio. Popular tools include Style Analytics' Portfolio Analyzer, Bloomberg's Portfolio and Risk Analytics tool, MSCI's Barra equity models, and tools from index provider S&P, among others. None of these tools follows the standard factor definitions that peer-reviewed research in financial economics has established.

Investors benefit from understanding and controlling their exposure to factors, only if these factors are reliable drivers of long-term returns. Factor definitions that have survived the scrutiny of hundreds of empirical studies and have been independently replicated in a large number of data sets are of course more reliable than ad-hoc constructs used for the specific purposes of a product provider.

Perhaps more importantly, the process by which factors are defined for popular analytics tools is inherently flawed. Common practices in designing these factors increase the risk of retaining factors which will ultimately be irrelevant as drivers of long-term returns.

This article will contrast factor definitions used in analytic tools offered to investors and contrast them with the standard academic factors. We also outline why the methodologies used in popular tools pose a high risk of ending up with irrelevant factors.

Are factors grounded in academic research?

Factor models link returns of any investment strategy to a set of common factors. In addition to the market factor, commonly-used factors include size, value, momentum, profitability and investment, which capture the difference of returns across firms with different characteristics. In financial economic research, a small number of models have become workhorses for analysing asset returns and fund manager performance, given the consensual understanding that they contain the factors that matter for asset returns. Providers of factor-based investment tools and strategies unequivocally claim that their factors are "grounded in academic research".[2] However, we will show that the factors used are instead completely inconsistent with the factors that are supported by a broad academic consensus.

5 or 500 factors?

Figure 1 provides an overview of the workhorse models in academic finance. There are three obvious insights.

- Different models use identical factor definitions;
- The number of factors is limited to about a handful of factors; and
- Factors are defined by a single variable.

These three properties ultimately mean that the different factor models draw on very few variables, which have been identified as persistent drivers of long-term returns.

In contrast, the factor tools from commercial providers typically include a proliferation of variables. MSCI's Factor Box draws on 41 different variables to capture the factor exposures of a given portfolio.[3] S&P markets a Factor Library which, despite including more than 500 variables[4] "encompassing millions of backtests", wants to help you "simplify your factor investing process". BlackRock proudly announces "thousands of factors" for its Aladdin Risk tool.[5]

This raises the question of why the standard models avoid such a proliferation of variables. First, the need for more factors is often rejected on empirical grounds. For example, Hanna and Ready (2005) show that using 71 factors does not add value over a model with two simple factors (book-to-market and momentum). Similarly, Hou, Xue and Zhang (2015) show that a model with four simple factors does a good job at capturing the returns across a set of nearly 80 factors. Second, academic research limits the number and complexity of factors because a parsimonious description of the return patterns is likely to be more robust. Increasing the number of variables will obviously improve fitting the model to a given data set but will also reduce the robustness when applying model results beyond the dataset of the initial tests. We will return to the question of robustness in more detail in the next section.

Transparent or opaque?

For commercially-available factor tools, it is extremely hard to get reliable information on how the factors are constructed and how exposures are estimated. Several studies report that they are unable to reproduce the results

1. Factor definitions in equity factor models that are predominant in the academic literature on mutual fund performance evaluation and asset pricing

	Factor definitions for					Number	
	Size	Value	Momentum	Profitability	Investment	of non-market factors	of variables per factor
Fama, French (1993)	Market cap	Book/ market				2	1
Carhart (1997)			Past returns			3	1
Chordia, Goyal, Saretto (2017)				Gross profit/ book equity	Asset growth	5	1
Fama, French (2014)						4	1
Hou, Xue, Zhang (2015)				Profit/book equity		3	1

1 Ang, A., W. Goetzmann and S. Schaefer (2009).

2 See Foundations of Factor Investing, MSCI Research Insight, December 2013.

3 See MSCI (2017).

4 See https://bit.ly/2OdIhTS

5 See https://bit.ly/2x8D8Vz

of commercial factor tools. The authors of one study[6] state that their "replication process becomes highly restrained" since the provider "omits a great amount of information". Another author[7] states he "cannot reproduce the model" because necessary information is "not disclosed".

We could try to be sympathetic towards this lack of disclosure because commercial providers may want to reasonably safeguard their development work from free-riding by copy-cat providers. However, it is useful to go back to the promise of factor investing. The starting point for being interested in factor exposures was to create transparency and 'understand the return drivers' of a portfolio. Available factor tools break this promise of transparency with a lack of disclosure on how the factors are constructed. It is not clear that an investor gains anything by seeing the estimated exposures to secretly defined factors. Understanding which factor labels drive returns without information on how the drivers themselves are constructed does not address the objective of factor investing. 'Understanding the return drivers' of course requires disclosure on the drivers themselves. Similarly, providing the breakdown of fat contained in a food product into different proprietary classifications, without being transparent on the definition of each type of fat, does not improve information on nutritious value.

In contrast to proprietary commercial factors, standard factor models are transparent on factor definitions and have been replicated in hundreds of independent studies.

Independent or interested?

Standard factor models have been used to analyse fund performance, impacts of corporate events on stock prices, and the structure of asset prices in thousands of empirical studies in peer-reviewed journals. It is safe to assume that these standard models resulting from the scrutiny of the entire academic community will not primarily reflect the self-interest of one author or product provider.

Proprietary factor definitions in commercial tools on the other hand could be driven by the interest of their providers. Indeed, providers instead try to establish proprietary and unproven factor definitions as standards to evaluate their competitors. For example, MSCI offers proprietary factor indices, and offers its Factor Box tool which draws on complex proprietary factors as a "standard [that] creates a common language and definitions around factors to be used by asset owners, managers, advisers, consultants and investors".[8]

The setting of standards should obviously draw on factor definitions that are both transparent to outside parties and externally validated. It would be hard to imagine for example that Toyota would propose a proprietary and undisclosed approach for crash tests of cars, while arguing that this test should be applied to its competitors when evaluating safety. Of course, the obvious risk would be that such a manufacturer might tweak its own cars in accordance with the specifics of the test, thus appearing favourable without any true gain in safety.

Data mining risks

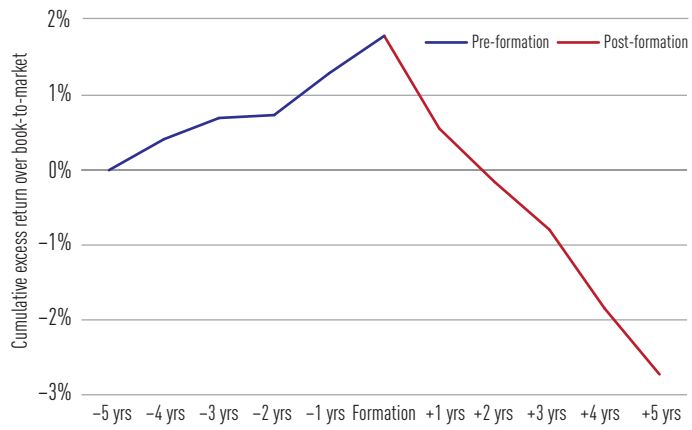
A perhaps more severe problem with commercial factor analytics tools is the process by which factors are defined. This process increases the risk of falsely identifying factors, due to weaknesses in the statistical analysis. In fact, providers will analyse a large set of candidate variables to define their factors. Given today's computing power and the large number of variables representing different firm characteristics, such an exercise makes it easy to find so-called 'factors' that work in the given dataset. However, these factors most likely will have no actual relevance outside the original dataset. That data-mining will lead to the identification of false factors is a problem that is well known to financial economists. Lo and MacKinlay (1990) provided an early warning against careless analysis: "[..] the more scrutiny a collection of data is subjected to, the more likely will interesting (spurious) patterns emerge".

Selection bias

It is well known that simply seeking out factors in the data without a concern for robustness will lead to the discovery of spurious factors. This is due to a 'selection bias' of choosing among a multitude of possible variables. Harvey et al (2016) document a total of 314 factors with positive historical risk premia showing that the discovery of the premium could be a result of data mining (ie, strong and statistically significant factor premia may be a result of many researchers searching through the same dataset to find publishable results). The practice of identifying merely empirical factors is known as 'factor fishing' (see Cochrane [2001]). Therefore, a key requirement for investors to accept factors as relevant in their investment process is that there be clear economic rationale as to why the exposure to this factor constitutes a systematic risk that requires a reward, and why it is likely to continue producing a positive risk premium (Kogan and Tian [2013]). In short, factors selected on the sole basis of past performance without considering any theoretical evidence are not robust and must not be expected to deliver similar premia in the future. This is emphasised by Harvey (2017), who argues that "economic plausibility must be part of the inference".

In addition, there are statistical tools to adjust results for the biases arising from testing a large number of variables. A recent study (Chordia et al [2017]) also emphasises the factor-fishing problem. They show that it is easy to find great new factors in backtests but such factors add no real value to standard factors. They create more than 2 million factors (levels, growth rates and ratios) from 156 accounting variables and assess whether these factors generate performance. While they find that there are 22,337 (!) great factors, the winning ratios do not make any economic sense (such as the ratio of common stock minus retained earnings to advertising expense). Moreover, these factors do not survive more careful vetting. None of the 20,000 factors that appear significant survives after adjusting for the well-known standard factors (size, value, momentum, profitability, investment and market) and for selection bias. These results emphasise that it is easy to discover new factors in the data if enough fishing is done, but such factors are neither economically meaningful nor statistically robust.

2. Comparison of cumulative relative returns of the average best in-sample alternative value strategy with respect to portfolios based on book-to-market



Results from Amenc et al (2016). This chart plots the cumulative excess returns of 10 annually-rebalanced cap-weighted value-tilted strategies with 50% stock selection out of the universe of 500 US stocks based on 10 alternative value strategies, with respect to a similarly constructed portfolio based on book-to-market. A five-year formation period is used to pick the best portfolio based on alternative value definitions and this portfolio is held for another five years. This is done every year for a total of 26 event studies. The chart plots the average outperformance pre- and post-formation with respect to the book-to-market portfolio. The alternative value definitions are earnings-to-price, cashflow-to-price, sales-to-price, dividend-to-price and payout-to-price, both plain-vanilla and sector-neutral versions for each.

Amenc et al (2016) provide a simple illustration for the risks of 'factor fishing'. They show that looking for the 'best' definition of value can easily lead to relying on promising in-sample results that do not hold out-of-sample. They ask whether we can do better than using the book-to-market measure for value by selecting among 10 alternative value metrics to form a value-tilted portfolio.

Figure 2 shows the out-of-sample decay of the data-mined value portfolios that rely on picking the best in-sample winners. The approach to defining value uses a five-year formation window at the end of which we select the best-performing strategy based on its in-sample performance. Then, the strategy is held for five years and the cumulative returns of this strategy are compared with respect to the portfolio based on the book-to-market measure.

The figure shows the average cumulative relative returns of the enhanced value strategy over standard value both pre- and post-formation. As the chart shows, picking the past winner yields cumulative outperformance over book-to-market of +1.79% in-sample. However, over the following five years, having picked the in-sample winner leads to cumulative underperformance of −2.72% out-of-sample. This is evidence that the backtest results obtained in such a variable picking exercise will appear inflated, relative to the results that can be generated out-of-sample.

Of course, tools which analyse exposure to factors with inflated backtest performance do not provide a meaningful picture of the factor-based performance that could truly be achieved. If factor performance is inflated, the return impact of exposures to these factors is also inflated.

Composite scores

In the discussion thus far, we emphasised that a stark problem arises from a practice where providers of factor tools select from among many

6 See Sousa Costa and Marques Mendes (2016).

7 See Guerard (2009).

8 See https://bit.ly/2N7rMfp

variables without many constraints. It turns out that the actual problem is even worse in practice. Providers of factor analytic tools do not stop their data-mining practices at the level of selecting single variables. Instead, they create complex composite factor definitions drawing on combinations of variables.

Research by Novy-Marx (2015) shows that the use of composite variables in the definition of factors yields a "particular pernicious form of data-snooping bias" – the overfitting bias. Intuitively, this bias arises because, in addition to screening the data for the best-performing variables, combining variables which give good backtest results provides even more flexibility to seek out spurious patterns in the data. The author concludes that "combining signals that backtest positively can yield impressive back-tested results, even when none of the signals employed to construct the composite signal has real power".

When combining variables to improve back-tested factor performance, providers can yet again increase flexibility for capturing spurious patterns in the data. Additional flexibility is easily achieved by attributing arbitrary weightings to the variables used in a composite definition. For a given combination of variables, changing the weight each variable receives in the factor definition may have a dramatic impact on factor returns. Figure 3 illustrates this point. The graph plots return differences over three-year horizons of two factor-tilted portfolios that draw on the same three variables to define a quality score. The only difference between the quality factor definitions is the weighting of the three component variables (profitability, leverage and investment). The difference in weightings used in the composite factor definitions leads to return differences that often exceed 5% annualised. Such pronounced differences suggest that, in a given sample, it is easy to improve factor returns by specifying arbitrary weightings for composite factor definitions.

3. Difference between annualised three-year rolling returns of two 'quality' portfolios using different weightings on the same set of variables

The weights in the two portfolios are as follows. Portfolio 1: investment 30%, profitability 60%, leverage 10%, Portfolio 2: investment 60%, profitability 30%, leverage 10%. Analysis is based on daily total returns in US dollars, from 31 December 1976 to 31 December 2016. The plotted line corresponds to the difference between three-year rolling annualised returns of the two 'quality' portfolios. Portfolios were formed by selecting stocks with the top 10% composite score and equal weighting them. The composite scores were defined by investment, profitability and leverage scores, weighted in two different ways: 60-30-10 and 30-60-10 respectively. The composite scores are standardised using cap-weighted mean and unit standard deviation.

4. Change in factor definitions over time

Provider	Scoring		Adjustments	
MSCI	**Value weighted (2010)**	**Enhanced value (2015)**	**2010**	**2015**
	● Sales, book value, earnings and cash earnings ● Past three-year average values ● Simple average across variables	● Price-to-book value, price-to-forward earnings, and enterprise value-to-cash from operations ● Current values ● Average of z-score for each variable	No sector control	Sector-relative scoring
FTSE Russell	**FTSE RAFI (2005)**	**Russell Fundamental (2012)**	**2005**	**2012**
	● Sales ● Operating income plus depreciation and amortisation ● Dividend ● Book value	● Sales ● Operating cashflow less dividends and buybacks ● Dividends plus buybacks	None	'Adjusting for financial leverage decreases the weight of companies with significant leverage'

For the MSCI methodologies, see Deploying Multi-Factor Index Allocations in Institutional Portfolios, Research Insight, MSCI, December 2013, and The MSCI Diversified Multi-Factor Indexes – Maximizing Factor Exposure While Controlling Volatility, Research Insight, MSCI, May 2015. For the FSTE Russell methodologies, see Construction and methodology Russell Fundamental Index® Series and Methodology Overview FTSE RAFI Index Series, available at www.ftse.com.

What do providers do?

Given the well-documented risk of biases, providers of factor tools should avoid data mining in the process of developing their factors. However, it is clear from the factor definitions used by providers that they tend to load heavily on data mining risk. As discussed above, the tools are based on a large number of composite variables that increase selection and overfitting bias. Moreover, many providers flexibly weight variables underlying their composite score. For example, Bloomberg uses a statistical procedure to weight the variables making up a composite factor[9] while MSCI uses a more haphazard approach involving "intuition [..], investors' expectations or other measures"[10] to attribute weights when combining variables into composites.

Product providers explicitly acknowledge that the guiding principle behind factor definitions is to analyse a large number of possible combinations in short data sets and then retain the factors that deliver the highest backtest performance. In fact, providers' product descriptions often read like a classical description of a data-snooping exercise, which is expected to lead to spurious results. For example, one provider states[11] that, when choosing among factor definitions, "adjustments could stem from examining factor volatilities, t-stats, information ratios", with an "emphasis on factor returns and information ratios". Another provider states that "factors are selected on the basis of the most significant t-stat values"[12], which corresponds to the technical definition of a procedure that maximises selection bias.

Inconsistency over time exacerbates data mining risks. Product providers show a great deal of flexibility in changing their factor definitions over time. Such frequent changes add yet another layer of flexibility to providers, thus increasing the risk of data snooping. Figure 4 illustrates this point with an overview of factor definitions used by two providers over time.

The frequent change of definitions is common practice among providers of tools. Obviously, frequent changes in the definition of factors suggest that these factors are not the persistent drivers of returns that investors are looking for. Factors such as value and momentum are precisely recognised as persistent factors because they deliver premia that are justified economically, and factor premia have been documented empirically, including for the 30-year period after the initial results were made publically available (see McLean and Pontiff [2016]). Factors that require frequent updating cannot be persistent factors and thus frequent updating is a sign of a lack of robustness.

This concern for robustness is not well understood by providers of analytic tools. One provider puts the concept on its head by claiming that "Factors [..] may be added, modified or removed, [..] to insure it accurately reflects a set of robust factors [..] at a given point in time".[13] The irony of relabelling spurious factors as "robust at a given point in time" reflects to what extent robustness is neglected in current product offerings.

While this section has tried to closely examine the different types of data-snooping risks inherent in popular analytic tools, it also appears obvious that such erratic factor definitions are not suited to supporting long-term investment decisions. Being open to the possibility of changing (non-robust) factors over time makes information about current factor exposures useless as a support for investment decisions, as these should rely on factors that will still be relevant drivers of performance in the future.

Redundant factors

For many factors used in popular analytics tools, it is well known that they fail to deliver a significant premium. For example, different analytics packages[14] include the dividend yield, leverage and sales growth as factors, while all of these factors have been shown not to deliver a significant premium (for the dividend yield, see Hou et al [2015], for leverage see Kyosev et al [2016], for growth see Lakonishok et al [1994]).

Factors may also be redundant with respect to consensual factors from the academic literature. In fact, many proprietary factors may have return effects, which can be explained away by the fact that they have exposures to standard factors (see Fama and French [1996]). We can illustrate this point by analysing the popular dividend yield factor.

Figure 5 shows that the dividend yield factor does not lead to significant returns. Moreover, when adjusting returns for the exposure to the standard value (book-to-market) effect, the dividend yield factor actually delivers negative returns.

9 See Sousa Costa and Marques Mendes (2016).
10 See MSCI (2018).
11 See MSCI (2018).
12 See FTSE (2014).
13 See MSCI (2018).
14 See, for example, Style Analytics (2018), available at https://bit.ly/2Nznq04

Popular analytic tools contain a large number of factors that do not deliver an independent long-term premium. This is bad news for investors who are using such tools to understand the long-term return drivers of their portfolios.

Getting your exposures wrong

In order to illustrate the risks of using non-standard factors we will look at the results of a regression of the returns of a composite quality factor on the returns of a set of academically-grounded and widely-accepted factors, including the quality-related factors of investment and profitability. This will allow us to assess the exposures of the practitioner quality factor to the academic factors and show that there is a clear mismatch between the intended and achieved exposures. As a practitioner quality factor we use the quality minus junk (QMJ) factor for which data is made available on the AQR website. AQR "define quality based on various measures of profitability, growth, safety and payout" to construct the factor.[15] The data on the regressors are taken from the data library of Kenneth French, where we use the five-factor model, including a market, size, value, profitability and investment factor, together with the momentum factor.[16] Contrary to QMJ, these factors have been extensively scrutinised in the academic literature.

Figure 6 shows the results using monthly return data for the period starting in July 1963 and ending in December 2017. The first two columns show the regression betas together with their t-statistic, while the third column shows how much of the annualised return of the QMJ factor can be attributed to the different regressors based on their average returns and their exposures. The last column shows the relative size of the impact each of the factors had on the QMJ returns over the period, calculated as the absolute value of its performance attribution divided by the sum of the absolute values of the performance attributions.

The first observation from these results is that the t-statistics point to a significant exposure to all the different factors. As would be expected for a quality factor, the exposure to profitability is the most clear with a beta of 0.64. However, the exposures to the market, size and value factors are also sizeable, but negative, with betas of –0.18, –0.17 and –0.19, respectively. These strong negative exposures to factors that are unrelated to quality is an important, presumably unintended, consequence of investing in the quality factor. These last three exposures are also larger in absolute value than the exposure to the investment factor, which would be expected to show a relatively stronger influence on a quality factor. Clearly, the composite quality factor exposes an investor to a range of standard factors other than the quality-related profitability and investment factors. When we look at the contribution of the different factors to the average annualised return of QMJ over the period, we see that only 26.84% of the impact on the quality factor returns comes from the quality-related factors profitability and investment. The vast majority of returns can be attributed to other standard factors or are unrelated to any factors. In fact, a big part of performance (43.45%) remains unexplained by any of the standard factors. Taken together, these results show that the composite quality factor is only moderately related to the academic profitability and investment factors, while a large part of its performance is either driven by other factors such as the market, or remains unexplained by the set of standard factors used in the model. An investor in this factor will thus expose himself or herself to a large amount of unintended exposures to factors unrelated to quality.

This risk is present in any non-standard factor. Proprietary factor definitions lead to a risk of misunderstanding factor exposures.

Conclusion: Reviving the promise of factor investing

Factors used in analytic tools show a stark mismatch with factors that have been documented by financial economists. Commercial factors are based on complex composite definitions which offer maximum flexibility. Providers use this flexibility to seek out the factors with the highest performance in a given dataset. Such practice allows spurious factors to be found. Spurious factors work well in a small dataset but will be useless in reality. Therefore, many factors that appear in popular analytic tools are likely false. In addition, providers are not transparent about the detailed specifications of their factors, and may face conflicts of interest.

We have shown that relying on proprietary factor definitions can lead to unintended exposures. For example, investors who tilt towards a composite quality factor will end up with a strategy where only about a quarter of returns are driven by exposure to the two well-documented quality factors (investment and profitability). This means that about three-quarters of returns are unrelated to quality factors, an obvious misalignment with the explicit choice to be exposed to quality factors (see figure 6). Even if the quality factors perform as expected by the investor, this performance will not necessarily be reflected in portfolio returns, which are mainly driven by other factors and idiosyncratic risks.

15 https://www.aqr.com/Insights/Datasets/Quality-Minus-Junk-Factors-Monthly

16 http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

5. The premium for dividend yield is insignificant

US Long-Term	Portfolios sorted by dividend yield					
	Low (Q1)	Quintile 2	Quintile 3	Quintile 4	Quintile 5	Q5–Q1
Average return	0.90%	0.94%	0.92%	1.08%	1.04%	0.14%
t-stat	–	–	–	–	–	1.07
CAPM model						
Unexplained	–0.05%	0.05%	0.04%	**0.21%**	0.14%	–0.09%
Market exposure	**1.05**	**0.94**	**0.94**	**0.93**	**0.97**	–0.08
R-squared	91.07%	92.24%	89.32%	86.50%	75.58%	0.93%
Fama-French three-factor model						
Unexplained	0.02%	0.08%	0.01%	**0.14%**	–0.01%	**–0.31%**
Market exposure	**1.09**	**0.98**	**0.95**	**0.91**	**0.89**	**–0.20**
Size (SMB)	**–0.04**	**–0.14**	**–0.15**	**–0.13**	–0.04	0.01
Value (HML)	**–0.22**	**–0.05**	**0.15**	**0.25**	**0.54**	**0.76**
R-squared	92.79%	93.08%	90.87%	89.53%	85.02%	38.04%

Analysis is based on monthly total returns in US dollars for the period 30 June 1927 to 31 December 2016. All the data comes from the K. French data library. Numbers that are statistically significant (p-value less than 5%) are formatted in bold.

6. Exposure of composite quality factor to standard factors

QMJ regression July 1963–December 2017	Beta	t-stat	Performance attribution	Impact on performance
Constant	0.04	6.84	3.60%	43.45%
Market	–0.18	–14.83	–0.94%	11.38%
Size	–0.17	–10.37	–0.42%	5.13%
Value	–0.19	–8.17	–0.72%	8.67%
Momentum	0.05	4.71	0.38%	4.54%
Profitability	0.64	28.13	1.75%	21.20%
Investment	0.14	4.23	0.47%	5.64%
R-squared	76.35%	Total	4.11%	100.00%

We have also shown the consequences of factor definitions that are created by fishing for the best in-sample factor performance. In our example above, tilting to an enhanced value factor leads to underperformance compared to the standard value factor of more than 2.5%. Perhaps more importantly, the backtest of such an enhanced value factor had actually suggested outperformance over the standard factor of more than 1.5%. Thus, the backtest had overstated the performance by more than 4% (see figure 2). For investors, using such enhanced proprietary factor definitions to define their factor allocation means that they face a severe risk of shortfall relative to expectations.

Available analytic tools thus do not deliver on the promise of factor investing, described almost a decade ago in the Norway study. Understanding the factor drivers of returns increases transparency and allows investors to formulate more explicit investment choices. However, being aware of exposures to useless factors, which have no reliable link with long-term returns, is equally useless.

Knowing about factor exposures is also a governance advantage. As pointed out by Ang and Kjaer (2011), an investor can use information on factor exposures to reduce the misalignment of interest of active managers. However, popular analytic tools for factor investing introduce their own governance problems. Relying on proprietary factors exposes investors to a provider-specific risk of conflicts of interests and a possibly flawed factor-finding process.

A good idea can easily be distorted when it is implemented with poor tools. For a meaningful contribution to transparency and better governance, factor investing should focus on persistent, transparent and externally validated factors. It is time to recall the good idea of factor investing.

References

Amenc, N., F; Ducoulombier, F. Goltz and J. Ulahel (2016). Ten Misconceptions about Smart Beta. EDHEC Risk Institute Publication (June).

Ang, A., W. Goetzmann and S. Schaefer (2009). Evaluation of Active Management of the Norwegian Government Pension Fund – Global.

Ang, A., and K.N. Kjaer (2011). Investing for the Long Run. Available at SSRN: https://ssrn.com/abstract=1958258 or http://dx.doi.org/10.2139/ssrn.1958258 (11 November).

Bender, J., R. Briand, D. Melas and R.A. Subramanian (2013). Foundations of Factor Investing. MSCI Research Insight (December).
Carhart, M. (1997). On Persistence of Mutual Fund Performance. *Journal of Finance* 52(1): 57–82.
Chordia, T., A. Goyal and A. Saretto (2017). p-Hacking: Evidence from Two Million Trading Strategies. Swiss Finance Institute Research Paper No. 17-37.
Cochrane, J. (2001). *Asset Pricing*. Princeton, NJ: Princeton University Press.
Fama, E.F. and K.R. French (1993). Common Risk Factors in the Returns on Stocks and Bonds. Journal of Financial Economics 33(1): 3-56.
Fama, E., and K.F. French (1996). Multifactor Explanations of Asset Pricing Anomalies. *Journal of Finance* 51(1): 55-84.
Fama, E.F., and K.R. French (2015). A Five-Factor Asset Pricing Model. *Journal of Financial Economics* 116(1): 1-22.
FTSE Russell (2014). Factor exposure indexes – Value factor? Available at https://www.ftserussell.com/sites/default/files/research/factor_exposure_indexes-value_factor_final.pdf.
Guerard, J. B. (2009). Markowitz and the Expanding Definition of Risk: Applications of Multi-factor Risk Models, Chapter 2 in: *Handbook of Portfolio Construction*, Springer.
Hanna, J. D., and M. J. Ready (2005). Profitable Predictability in the Cross Section of Stock Returns. *Journal of Financial Economics* 78(3): 463–505.
Harvey, C. (2017). Presidential Address: The Scientific Outlook in Financial Economics. *Journal of Finance* 72(4): 1399–1440.
Harvey, C., Y. Liu and H. Zhu (2016). ... and the Cross-Section of Expected Returns. *Review of Financial Studies* 29 (1): 5-68.
Hou, K., C. Xue and L. Zhang (2015). Digesting Anomalies: An Investment Approach. *Review of Financial Studies* 28(3): 650–705.
Kogan, L., and M. Tian (2013). Firm Characteristics and Empirical Factor Models: A Data-Mining Experiment. MIT Working Paper.
Kyosev, G., M.X. Hanauer, J. Huij and S. Lansdorp (2016). Quality Investing – Industry versus Academic Definitions. Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2794807 (13 June).
Lakonishok, J., A. Shleifer and R.W. Vishny (1994). Contrarian Investment, Extrapolation, and Risk. *Journal of Finance* 49(5): 1541-1578.
Lo, A.W., and C. MacKinlay (1990). Data Snooping biases in Tests of Financial Asset Pricing Models. *Review of Financial Studies* 3(3): 431–467.
McLean, R. D. and J. Pontiff (2016). Does Academic Research Destroy Stock Return Predictability? *Journal of Finance* 71(1): 5-32.
MSCI (2017). Use of the Global Equity Model (GEM LT) In MSCI Index Construction. MSCI Presentation (January), available at https://bit.ly/2x2EhOx.
MSCI (2018). Introducing MSCI FaCS – A New Factor Classification Standard for Equity Portfolios (January).
Novy-Marx, R. (2015). Backtesting Strategies Based on Multiple Signals. Working Paper. National Bureau of Economic Research.
Sousa Costa, R., and M. Marques Mendes (2016). Understanding Multi-Asset Factor Models. Nova School of Business and Economics. Presentation available at: https://bit.ly/2p1mnbd.

Mismeasurement of factor exposures in score-based analytics tools

Ashish Lodh, Deputy Research Director, ERI Scientific Beta

The use of factor scores instead of factor betas for the measurement of portfolio factor exposures is a cause of concern because factor investing literature uses beta-based models for factor premia tests and for portfolio style analysis.

The major drawback factor scores suffer from is 'double counting' of exposures, which is due to their lack of regard for the correlation structure of factors. This makes factor scores a very poor proxy for factor betas.

Another common practice is to combine single factor scores into a composite factor score. This leads to additional problems because combining two scores that have a skewed joint distribution disproportionately favours one factor over another and using these composite definitions to measure score exposures leads to misidentification of factor tilts.

The rise of passive factor investing products has been good news for the investing community overall but it has also highlighted a set of challenges and pitfalls that investors need to be cautious about. One such challenge, which has received a lot of attention recently, is to identify the persistent drivers of risk and return from a constantly increasing pool of proposed factors (Harvey et al [2016]). Another issue that is often overlooked and warrants more discussion is the question of factor exposure measurement. Many factor analytics providers propose tools that rely on quantifying and reporting portfolio characteristics in the form of factor scores rather than focusing on beta exposures. Factor scores are easy to compute, they do not require the history of portfolio returns and they provide an instantaneous measure of several portfolio characteristics. Although one can see the appeal of simplicity in working with factor scores, they should not be treated as a substitute for factor betas because they do not provide the same information. This distinction is important because portfolio returns are driven by its factor betas and not factor score tilts. This article details the problems associated with the use of factor scores in portfolio construction and portfolio analysis.

The factor models in asset pricing literature are the cornerstone of portfolio construction and performance evaluation. The objective of any empirical factor model is to provide a framework to show the relationship between the risk and expected return of a risky portfolio. The CAPM (Sharpe [1964], Lintner [1965]), which is the oldest and arguably most widely used factor model, postulates that portfolio risk is composed of systematic and unsystematic components and that only systematic risk, which is the market risk, is rewarded with returns. The model has been extended over the years with the addition of more risk factors such as size and value (Fama and French [1993]), momentum (Carhart [1997]), and profitability and investment factors (Fama and French [2015]). All these factor models differ on the definition of systematic risk factors, but they all have one thing in common; they are all beta models based on firm characteristics that are estimated using regression techniques.

In order to qualify as an acceptable factor model, it must undergo time series and cross-sectional tests to determine if the beta risk of the proposed factor is priced or not. Two commonly used factor-pricing tests are the two-pass OLS methods developed by Fama and Macbeth (1973) and Black, Jensen and Scholes (1972). In the first pass, the time series regression, a set of test portfolios are regressed against factors to obtain their factor betas. In the second pass the cross section of test portfolio returns is regressed against their factor betas over time to estimate the associated risk premium. For given portfolio returns (Y) and factor return matrix (X), the OLS estimates of betas are derived as:

$$Y = X \cdot \beta + \varepsilon$$

$$\hat{\beta} = \left(X' \cdot X\right)^{-1} \cdot X' \cdot Y$$

Although beta models based on risk explanations are more popular, there is a strand of the literature that uses characteristic-based models under the assumption that factor anomalies are caused by mispricing and after controlling for firm characteristics the positive relationship between expected returns and HML and SMB factors disappears (Lakonishok, Shleifer and Vishny [1994] and Daniel and Titman [1997]). The characteristic-based

NEW BLENDED-LEARNING PROGRAMME

Capitalise on a Unique and Flexible Course

Explore Asset Allocation Concepts and Techniques at your own pace, relying on e-learning material developed by EDHEC-Risk Institute

Participate in case studies at our London campus with Professor Martellini on March 13th, 2019

Learning Objectives

- Understanding the Value of Financial Risk Management in the Investment Management Process
- Defining the Three Possible Approaches to Risk Management: Diversification, Hedging and Insurance
- Introducing Liability-Driven Investing and Goal-Based Investing
- Understanding the Benefits of Risk Allocation, Factor Investing and Smart Betas
- Understanding Improved Forms of Target-Date Funds and Retirement Solutions

Exclusive Expertise

developed by

EDHEC-RISK Institute

For further information and registration, please contact
Caroline Prévost: **caroline.prevost@edhec-risk.com**
or on: **+33 493 183 496**

approach to portfolio evaluation compares the performance of stocks against a benchmark that consists of stocks with similar characteristics. Daniel and Titman [1997] propose a 'characteristics-based selectivity measure' which is defined as: $W_{j,t-1}$ is the weight of j-th stock, $R_{j,t}$ is the month t return of stock j, $R_t^{bj,t-1}$ is the month t return of the characteristic-based benchmark portfolio that is matched to stock j during month t–1):

$$CS_t = \sum_{j=1}^{N} W_{j,t-1} \cdot \left(R_{j,t} - R_t^{b_j,t-1}\right)$$

Since factor betas estimated from OLS regressions depend on the covariance structure of factors, they take factor correlation into account. On the other hand, characteristics-based models suggest that there is no link between covariance and expected returns. This is an important difference between the two approaches and its implications are discussed in detail in this article. Another advantage of betas obtained from OLS regressions is that the regression diagnostics associated with this regression are directly available, allowing for an appreciation of the quality of the relationship. For example, a high R-squared means the factors are the main drivers of the return variability of portfolio returns, and a low (significant) p-value means that there is a fair amount of statistical certainty that the portfolio returns are linked to factor betas as opposed to coming from chance alone. This is a notable difference with scores, which are observable but do not allow for direct insights on the relevance of the score for the strategy.

Commonly used score-based tools

We briefly describe the scoring methodology used by two major providers of factor analytics to evaluate the factor characteristics of equity portfolios. The MSCI FaCS framework is based on the Barra equity factor risk model and it recognises a total of 16 style factors that fall into eight broad factor groups – value, size, momentum, volatility, quality, yield, growth and liquidity. The following are the main steps involved in the construction of factor scores for stocks and portfolios:

- Raw values of factor descriptors are considered, outliers are removed and the remaining values winsorised within three standard deviations.
- Raw scores are converted to standardised z-scores to have a market-cap-weighted mean of zero and a unit standard deviation.
- Factor scores are obtained from the linear combination of descriptor scores.
- Factor scores are standardised again to have a market-cap-weighted mean of zero and a unit standard deviation.
- Portfolio-level factor exposure is a weighted average of stock level exposures.

One problem with this analysis is that the linear combination of descriptor scores is not well defined. It is based on "a combination of intuition and statistical metrics" and is sometimes determined by backtest performance, which makes it sample dependent. The standardisation of factor scores is also subject to arbitrary country adjustments. Raw descriptors based on prices (momentum, beta, residual volatility) are standardised on a global universe; others based on fundamentals are standardised based on a country-specific mean, but using a global standard deviation. Another issue with the framework is the possible addition, deletion and modification of factor groups in the future, which is not consistent with the fact that factor premia should be persistent over long periods and factor definitions should not evolve with time.

Style Analytics is another provider of portfolio factor analytics that purely uses scores to define style tilts. Its scoring method is described below:

- Stock-level raw factor scores are taken and outliers removed.
- The raw factor tilt is normalised by taking the difference between the portfolio's weighted average factor and the benchmark's weighted average factor, divided by the weighted standard deviation of the factor. The normalised scores show the direction of the factor tilt relative to the benchmark but do not indicate the level of significance.
- Factor tilts are standardised using a "sample size adjustment" to provide a measure of the strength of the portfolio score relative to the benchmark. Standard deviations of weighted factor averages across portfolios of similar construction are used for normalisation.

Style Analytics provides a set of rules to interpret the significance level of factors tilts. The rules state that factor tilts between –0.5 and +0.5 are "probably not significant"; those between –0.5 and –1.0 and +0.5 and +1.0 "exist but may not be significant"; and those below –1.0 and above +1.0 are significant. The problem with the methodology is that the sample size adjustment penalises the scores of broad market portfolios to make them comparable with more concentrated portfolios on a score-to-score basis, when there is no such requirement in factor beta measurement theory. In addition, the significance tests are not based on any statistical theory; they are rather just a rule of thumb that is supposed to work in most circumstances but not always. On the other hand, in a multivariate regression analysis, the coefficients (beta) are always accompanied by their p-values and it is possible to obtain high betas with low significance or smaller betas with high significance. The next two sections provide some stylised examples to show the limits of using solely factor scores in the design and analysis of factor portfolios.

The problem with factor scoring

The major drawback of score-based analysis is that scores ignore correlation across factors, leading to 'double counting' of exposures. It is well known that the six risk factors are correlated to each other and this correlation changes with time. Factor betas from a multivariate regression, by indicating the marginal impact of a factor given the presence of other factors, take into account the interaction across factors. On the other hand, any score-based technique completely ignores this important aspect altogether.

Below we demonstrate, through a simple example, why it is better to take this interaction into account. We show that when designing allocations that target specific factor exposures, a beta-based approach is more suitable than a score-based approach. A score-based approach would lead to instability in terms of factor betas. Even if a target score is achieved, the score-based strategy might pick up exposures to other factors depending on interaction effects.

We construct a portfolio that has an exposure of 1.00 to the market factor, a constant beta of 0.75 to the low investment factor and zero exposure to the other five factors. We do this by using an overlay of the long/short low investment factor on the broad cap-weighted index. The long/short low investment factor is a daily-rebalanced portfolio with 30% equally weighted low investment stocks in the long leg and 30% equally weighted high investment stocks in the short leg. The weights of this 'target beta' portfolio are given by:

$$W_P = W_{CW} + 0.75 * \left[W_{LInv} - W_{HInv}\right]$$

This 'target beta' portfolio is compared to a 'target score' portfolio that targets a constant low investment score. To make the two portfolios comparable, the target low investment score matches the long-term low investment score of the 'target beta' portfolio. The other five factor scores have a target of zero to make it a pure low investment portfolio in terms of scores. The portfolio is rebalanced quarterly. The portfolio optimisation is defined as follows:

$$W_P = \arg\max\left[\frac{1}{W' \cdot W}\right]\begin{cases} \sum_{i=1}^{N} w_i = 1 \\ -0.05 \le w_i \le +0.05 \;\forall\, i \\ W \cdot \dot{F} = \left[0\,0\,0\,0\,0\; S_{LInv}^{\text{Target}}\right] \end{cases}$$

N is the number of stocks in the universe.
$\dot{F}$ is the Nx6 matrix of the stock level factor scores for the six factors.[1]
S_{LInv}^{Target} is set to be 1.44.

This 'target score' portfolio is comparable to the 'target beta' portfolio, because both portfolios obtain the same long-term average z-score for the low investment factor. The difference between the two portfolios is that one of them explicitly controls factor exposures in terms of betas, while the other controls factor exposures in terms of score. This is exactly the difference we wish to analyse in this article.

Figure 1a shows the average factor scores and full period factor betas of the 'target beta' portfolio. The 'target beta' portfolio or the pure low investment factor index, which has zero HML and L.VOL betas by design, appears to have value and low volatility tilts when looked at through the lens of scores. The low investment strategy with a constant beta of 0.75 shows very high value and low volatility scores because these two factors are highly correlated to the low investment factor on average over the long term.

Figure 1b shows the time varying score exposures of the same strategy. The low investment z-score of the strategy is highly unstable and ranges from 0.70 to 1.75 with a standard deviation of 0.23. It is surprising to observe that the portfolio exhibits a higher undesirable low volatility beta than the desirable low investment beta. The other five factor scores are also significantly unstable despite constant zero exposure to them by construction.

Figure 2a shows the average factor scores and full period factor betas of the 'target score' portfolio. The low investment strategy with a constant z-score of 1.44 exhibits low investment beta of 0.38, which is inferior to the low investment beta of 0.75 that was achieved by the 'target beta' portfolio for the same level of low investment z-score. In other words, these two portfolios that appear to be equally good low investment portfolios going by their scores in fact tilt towards the low investment factor with very different magnitudes. Also, due to the previously discussed issue of ignored correlation, the low investment strategy with a constant z-score ends up with a positive exposure (+0.12) to the HML factor and a negative exposure (–0.21) to the low volatility factor. Figure 2b sheds more light on the stability of multivariate regression betas and highlights the variation of HML and low volatility betas

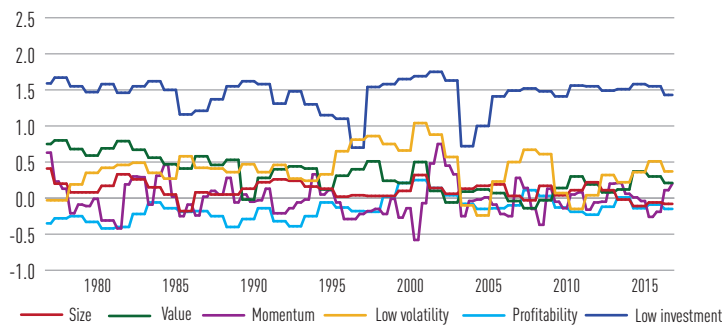
1 All factor scores are standardised using cap-weighted mean and unit standard deviation. The resulting z-scores are then winsorised to fall between –3.0 and +3.0. Scoring is performed bi-yearly for the momentum factor and yearly for all other factors.

1a. Scores and betas of the low investment strategy with a constant beta of 0.75

	Size	Value	Momentum	Low volatility	High profitability	Low investment
Mean z-score	0.10	0.32	–0.01	0.40	–0.15	1.44
Standard deviation z-score	0.11	0.25	0.23	0.28	0.16	0.23
Beta	0.00	0.00	0.00	0.00	0.00	**0.75**
Standard deviation beta	0.00	0.00	0.00	0.00	0.00	0.00
5th percentile	0.00	0.00	0.00	0.00	0.00	0.75
95th percentile	0.00	0.00	0.00	0.00	0.00	0.75

The analysis is done for the period 31 December 1976 to 31 December 2016. All factor scores are standardised using cap-weighted mean and unit standard deviation. The resulting z-scores are then winsorised to fall between –3.0 and +3.0. Score exposures are the average across 160 rebalancings. Regressions are done using weekly total returns in US dollars and a seven-factor model from Scientific Beta. Coefficients significant at 5% p-value are highlighted in bold. The standard deviation of betas is calculated using rolling seven-factor regressions that use a rolling period of two years and step size of one month.

1b. Time-varying scores of the low investment strategy with a constant beta of 0.75



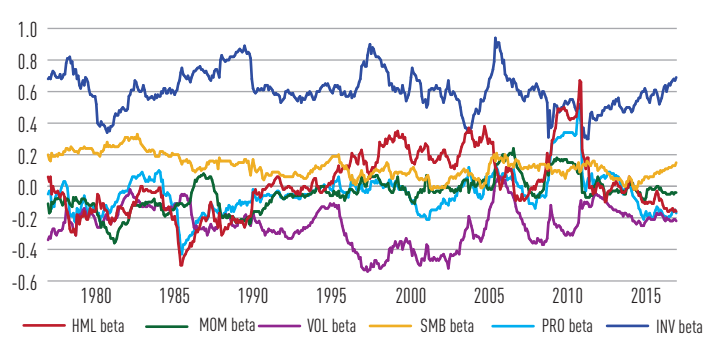
The analysis is done for the period 31 December 1976 to 31 December 2016. All factor scores are standardised using cap-weighted mean and unit standard deviation. The resulting z-scores are then winsorised to fall between –3.0 and +3.0.

2a. Scores and betas of the low investment strategy with a constant z-score of 1.44

	Size	Value	Momentum	Low volatility	High profitability	Low investment
Mean z-score	0.00	0.00	0.00	0.00	0.00	1.44
Standard deviation z-score	0.00	0.00	0.00	0.00	0.00	0.00
Beta	**0.08**	**0.12**	**-0.02**	**-0.21**	**0.03**	**0.38**
Standard deviation beta	0.07	0.20	0.10	0.13	0.13	0.12
5th percentile	0.01	-0.26	-0.23	-0.47	-0.20	0.39
95th percentile	0.25	0.35	0.15	-0.06	0.23	0.83

The analysis is done for the period 31 December 1976 to 31 December 2016. All factor scores are standardised using cap-weighted mean and unit standard deviation. The resulting z-scores are then winsorised to fall between –3.0 and +3.0. Score exposures are the average across 160 rebalancings. Regressions are done using weekly total returns in US dollars and a seven-factor model from Scientific Beta. Coefficients significant at 5% p-value are highlighted in bold. The standard deviation of betas is calculated using rolling seven-factor regressions that use a rolling period of two years and step size of one month.

2b. Rolling betas of the low investment strategy with a constant z-score of 1.44



The analysis is done for the period 31 December 1976 to 31 December 2016. Regressions are done using weekly total returns in US dollars and a seven-factor model from Scientific Beta. The rolling seven-factor regressions use a rolling period of two years and step size of one month.

3. Performance, risk and factor performance attribution

US 1976–2016	Broad CW index	Target beta strategy (Investment beta = 0.75)	Target score strategy (Investment z-score = 1.44)
Annualised returns	10.86%	13.73%	13.91%
Annualised volatility	17.07%	15.07%	16.38%
Sharpe ratio	0.35	0.59	0.55
Maximum drawdown	54.3%	51.4%	63.3%
Annualised unexplained	0.00%	0.07%	**1.87%**
Market beta	**1.00**	**1.00**	**0.92**
SMB beta	0.00	0.00	**0.08**
HML beta	0.00	0.00	**0.12**
WML beta	0.00	0.00	**–0.02**
L VOL beta	0.00	0.00	**–0.21**
H PRF beta	0.00	0.00	**0.03**
L INV beta	0.00	**0.75**	**0.38**
R-squared	100%	100%	94%
Unexplained	0.00%	0.90%	1.89%
Returns market	5.75%	5.75%	5.31%
Returns SMB	0.00%	0.00%	0.12%
Returns HML	0.00%	0.00%	–0.03%
Returns WML	0.00%	0.00%	–0.05%
Returns L VOL	0.00%	0.00%	0.40%
Returns H PRF	0.00%	0.00%	0.08%
Returns L INV	0.00%	1.85%	0.94%
Specific risk	0.00%	0.23%	3.87%

The analysis is done for the period 31 December 1976 to 31 December 2016. All statistics are annualised. Regressions are done using weekly total returns in USdollars and a seven-factor model from Scientific Beta. Coefficients significant at 5% p-value are highlighted in bold. The factor performance attribution methodology breaks down the total excess returns of a strategy portfolio (over the risk-free rate) into several components related to the performance of systematic risk factors.

in particular. There are times (2009–11) when the portfolio resembles a multi-factor portfolio with value and low investment as leading tilts.

Figure 3 presents a snapshot of the total performance and its attribution to the risk factors for the two strategies – the low investment strategy with a constant beta of 0.75 ('target beta') and the low investment strategy with a constant z-score of 1.44 ('target score'). A quick comparison of r-squared from the seven-factor model shows that the market and low investment factors are indeed the main drivers of return variability for the 'target beta' strategy (R^2 = 100%) while these seven factors do not completely capture the return variability of the 'target score' strategy (R^2 = 94%).

The 'target score' strategy exhibits a low investment beta of 0.38 but also has exposures to other factors, the z-scores of which are set to zero. A performance attribution exercise provides the performance implications of the unintended exposures to the other factors. The low investment factor accounts for 0.94% of returns over the long term, followed by 0.40% coming from the low volatility factor and 0.08% from the profitability factor. In addition to having undesired and unstable factor exposures, the 'target score' portfolio also exhibits extremely high levels of specific risk. The specific risk, which is calculated as the volatility of the residual terms from the seven-factor regression, is 0.23% for the 'target beta' portfolio in contrast to 3.87% for the 'target score' portfolio. Due to this high level of unrewarded risk, this strategy delivers a lower Sharpe ratio and a very high level of maximum drawdown (63.3%).

Next, we investigate in more detail the impact of factor correlations on score exposures by using an example of a portfolio that targets multiple factor betas simultaneously. The objective of this exercise is to understand how exactly changing correlation between factors affects a portfolio's factor scores. We construct a portfolio that has an exposure of 1.00 to the market factor, a constant beta of 0.50 to each of the value and momentum factors and zero exposure to the other four factors. The value and momentum factors are chosen because they have low correlation on average and their correlation is known to change over time (Asness et al [2013]). We use the same overlay methodology as in the previous example. The weights of this 'value-momentum' strategy are given by:

$$W_P = W_{CW} + -0.50 * [W_{H.Value} - W_{L.Value}] + 0.50 * [W_{H.Mom} - W_{L.Mom}]$$

Figure 4a reports the average scores and full period factor betas of this portfolio. It shows that in addition to having high score exposures to the value and momentum factors, the portfolio also shows residual exposures to other factors, especially very high negative exposure to the high profitability factor. To understand the relationship between 'double counting' and correlation between factors, we show (figure 4b) the time-varying value and momentum scores of the value-momentum strategy alongside the rolling correlation between the value and momentum risk factors.[2]

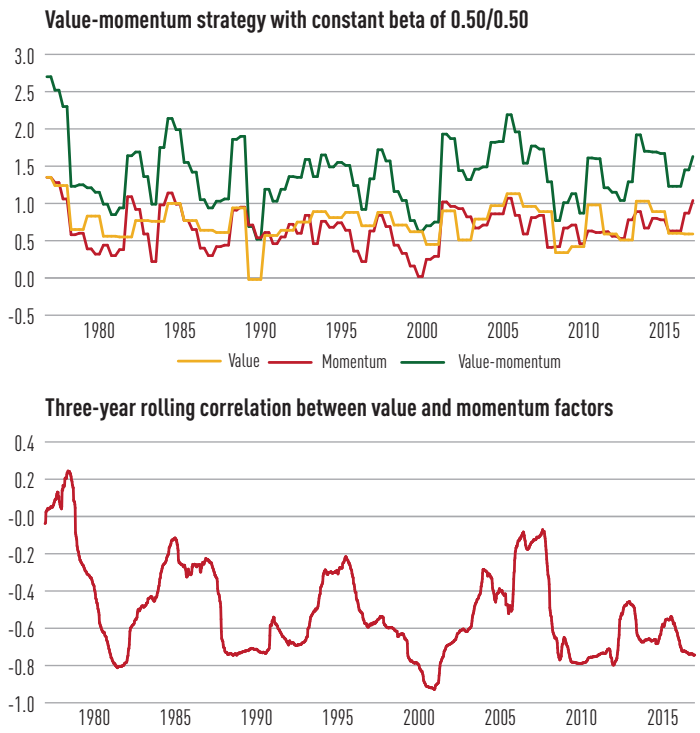
2 The value and momentum risk factors are the long/short risk factors from Scientific Beta that are used on a seven-factor regression model.

4a. Scores and betas of the value-momentum strategy with constant betas of 0.50/0.50

	Size	Value	Momentum	Low volatility	High profitability	Low investment
Mean z-score	0.12	0.74	0.66	0.22	-0.61	0.19
Standard deviation z-score	0.15	0.24	0.26	0.27	0.16	0.22
Beta	0.00	**0.50**	**0.50**	0.00	0.00	0.00
Standard deviation beta	0.00	0.00	0.00	0.00	0.00	0.00
5th percentile	0.00	0.50	0.50	0.00	0.00	0.00
95th percentile	0.00	0.50	0.50	0.00	0.00	0.00

The analysis is done for the period 31 December 1976 to 31 December 2016. All factor scores are standardised using cap-weighted mean and unit standard deviation. The resulting z-scores are then winsorised to fall between –3.0 and +3.0. Score exposures are the average across 160 rebalancings. Regressions are done using weekly total returns in US dollars and a seven-factor model from Scientific Beta. Coefficients significant at 5% p-value are highlighted in bold. The standard deviation of betas is calculated using rolling seven-factor regressions that use a rolling period of two years and step size of one month.

4b. Time-varying scores of the value-momentum strategy with constant betas of 0.50/0.50



The analysis is done for the period 31 December 1976 to 31 December 2016. All factor scores are standardised using cap-weighted mean and unit standard deviation. The resulting z-scores are then winsorised to fall between –3.0 and +3.0.

5. Examples of commonly used composite factor definitions

	MSCI FaCS	Style Analytics
Value factor	● Book to price ● Earnings yield ● Reversal	● Book to price ● Dividend yield ● Earnings yield ● Cash flow yield ● Free cash flow yield ● Sales to price ● EBITDA to price ● Sales to EV ● EBITDA to EV ● IBES dividend yield, earnings yield, sales yield
Quality factor	● Leverage ● Profitability ● Earnings variability ● Earnings quality ● Investment quality	● Earnings Growth Stability ● Sales Growth Stability ● Low Accruals ● Low Gearing ● Returns Stability

Source: MSCI (https://www.msci.com/facs), Style Analytics (https://www.styleanalytics.com)

6. Composite score is biased due to distributional properties

		Profitability score	
Momentum score		**Low**	**High**
	High	16%	70%
	Low	0%	14%
		Profitability score	
Low investment score		**Low**	**High**
	High	2%	70%
	Low	0%	28%

High and low quadrants are separated by median z-scores. Composites of the two variables are formed by averaging the two z-scores and a top 10% of stocks based on the composite score is selected and they are highlighted in red circles. The scores are based on the rebalancing date 16 December 2016. All factor scores are standardised using cap-weighted mean and unit standard deviation. The resulting z-scores are then winsorised to fall between –3.0 and +3.0.

The multivariate regression analysis, with which portfolio construction is done, takes this into account and provides a strong and constant exposure to both the value and momentum factors. On the other hand, the score-based analysis, being single dimensional in each factor, falls into the trap of varying correlation and shows an inaccurate picture of varying factor exposures. In the times of low correlations the value score of momentum stocks and the momentum scores of value stocks are weaker. As a result, every time the correlation between the two factors drops, the score exposure of either one of the factors is also reduced, which in turn brings down the aggregate score exposure.

Here it is important to realise that low correlation across factors is in fact advantageous to investors from the point of view of risk management. Combining factors tilts that have low correlation is the key to minimising total portfolio risk and improving risk adjusted returns. So a metric that artificially lowers aggregate exposure just because factors become less correlated works against the multi-factor objective and therefore is unsuitable for factor exposure assessment.

The problem with composite factor scores

Having explained the shortcomings of using factor scores in the previous section, we discuss the additional problem that arises from the use of composite scores, which is the misidentification of factor tilts.

Figure 5 provides examples of factor score composites for Value and Quality factors used in portfolio analytics reporting by some leading providers. Not only does the use of proprietary/enhanced factor definitions and the use of too many factors pose serious questions about the relationship of these factors to the real Value and Profitability factors (Fama and French [1993] and Fama and French [2015]) and about the existence of their factor premia, but the very notion of using composites comes with its own drawbacks.

Below we discuss the problems with score composites in detail. In the first part, we show the drawbacks of using a factor composite score in the stock selection process. In the second part, we discuss how the use of score composites to analyse portfolio exposures can lead to misidentification of score tilts.

Figure 6 details the problem of composite scoring by showing the overlap matrix in the above two examples. It shows the percentage of stocks that come from high/low factor scoring brackets in two very different scenarios; when the distribution is symmetrical (momentum and profitability) and when the distribution is skewed (profitability and investment). It shows that 14% of high composite stocks originate from a poor momentum score and 16% stem from a poor profitability score bucket, which means that a stock with a low score in one of the factors still has a chance to attain a high composite score, thanks to the symmetrical distribution of scores. However, in the case of skewed distribution only 2% of high composite stocks originate from a poor profitability score and 28% of them from a poor investment score bucket. This means the stocks that score poorly on the profitability score cannot compensate with a good investment score.

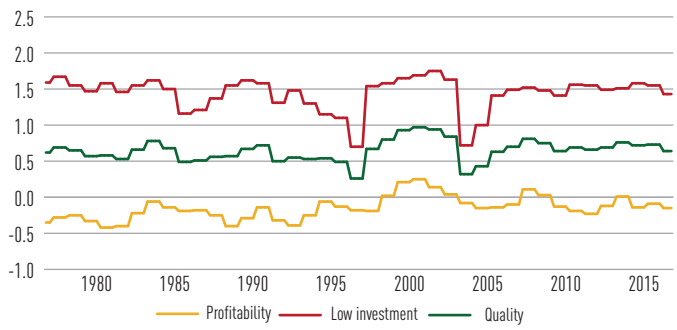
Next, we show how lumping different factors together and using this definition to measure factor scores hides the true underlying exposures of a portfolio. We take the example of the pure low investment-tilted portfolio (with a constant low investment beta of 0.75) and look at its factor scores while combining investment and profitability together into one factor score – a quality score. Figure 7a shows that the pure low investment-tilted portfolio has a comparatively weak quality score but significant value and volatility scores, which is a classic example of misclassification of tilts. Figure 7b explains the reason behind this weak quality exposure. Although the pure low investment-tilted portfolio has a high low investment score, it simultaneously has a very low high profitability score. This is because the quality composite does not take the correlation between profitability and investment into account.

7a. Scores of the low investment strategy with a constant beta of 0.75

	Size	Value	Momentum	Low volatility	Quality
Mean z-score	0.10	0.32	–0.01	0.40	0.65

The analysis is done for the period 31 December 1976 to 31 December 2016. All factor scores are standardised using cap-weighted mean and unit standard deviation. The resulting z-scores are then winsorised to fall between –3.0 and +3.0. Score exposures are the average across 160 rebalancings.

7b. Time-varying betas of the low investment strategy with a constant beta of 0.75



The analysis is done for the period 31 December 1976 to 31 December 2016. All factor scores are standardised using cap-weighted mean and unit standard deviation. The resulting z-scores are then winsorised to fall between –3.0 and +3.0.

7c. Selected quarter scores of the low investment strategy with a constant beta of 0.75

Z-scores	Size	Value	Momentum	Low volatility	Quality
March 1982	0.33	**0.79**	0.19	0.46	0.53
March 1986	–0.18	**0.41**	–0.09	**0.58**	**0.49**
March 1997	0.04	0.40	–0.22	**0.81**	0.26
December 2001	0.14	0.10	**0.75**	**0.88**	0.94

The analysis is done for the period 31 December 1976 to 31 December 2016. All factor scores are standardised using cap-weighted mean and unit standard deviation. The resulting z-scores are then winsorised to fall between –3.0 and +3.0.

8. Factor contribution

		Target beta strategy (Investment beta = 0.75)		Target score strategy (Investment z-score = 1.44)	
Year 1998	**Factor premia**	**Factor beta**	**Factor contribution**	**Factor beta**	**Factor contribution**
SMB	–25.3%	0.00	0.0%	0.10	–2.5%
HML	–23.7%	0.00	0.0%	0.20	–4.8%
WML	25.0%	0.00	0.0%	0.00	0.0%
L VOL	–0.8%	0.00	0.0%	–0.13	0.1%
H PRF	8.1%	0.00	0.0%	–0.09	–0.7%
L INV	4.2%	0.75	3.1%	0.49	2.0%
All factors	**–**	**–**	**3.1%**	**–**	**–5.8%**

		Target beta strategy (Investment beta = 0.75)		Target score strategy (Investment z-score = 1.44)	
Year 1998	**Factor premia**	**Factor beta**	**Factor contribution**	**Factor beta**	**Factor contribution**
SMB	–4.9%	0.00	0.0%	0.10	–0.5%
HML	–10.4%	0.00	0.0%	0.23	–2.4%
WML	28.7%	0.00	0.0%	–0.04	–1.2%
L VOL	24.6%	0.00	0.0%	–0.21	–5.2%
H PRF	22.0%	0.00	0.0%	–0.06	–1.4%
L INV	21.5%	0.75	16.1%	0.70	15.0%
All factors	**–**	**–**	**16.1%**	**–**	**–4.4%**

The low investment strategy with a constant beta of 0.75 is compared with the low investment strategy with a constant z-score of 1.44. The analysis is done for the period 31 December 1976 to 31 December 2016. Regressions are done using weekly total returns in US dollars and a seven-factor model from Scientific Beta.

Figure 7c shows that the pure low investment-tilted portfolio is identified as being multi-factor if one were to base the reporting on factor score analysis. It appears to be dominated by value and low volatility scores in certain periods. We take a closer look at the portfolio and pick some periods where the score exposures are not in line with expectations. The quality score goes from 0.26 in March 1997 to 0.94 in just three years. In periods like March 1982 and March 1997 the score exposure to other untargeted factors, value and low volatility respectively, was far greater than the exposure to the quality factor.

Conclusion

Beta-based factor models (like the CAPM and the Fama-French three-factor or five-factor models) lie at the foundation of factor investing research and are widely used in the academic community in a variety of functions ranging from validating new factor findings and portfolio optimisation to fund performance appraisal. However, most popular factor analysis tools used by investors deviate from the models used in research because they choose to use factor scores instead of betas. Although scores are easy to compute and present a point-in-time snapshot of portfolio characteristics, factor scores have serious shortcomings when it comes to factor exposure measurement.

Targeting factor scores leads to portfolios that exhibit unstable exposure to the target factor and unintended exposure to other factors when analysed using a multivariate regression model. For example, we have shown above that a strategy that targets a constant low investment score ends up with a highly variable low investment beta ranging from 0.39 to 0.83. There are periods when this strategy shows higher value beta (0.66) than low investment beta (0.42). Thus an investor would end up with an exposure to value that is not only unintended, but also dominates the targeted (low investment) exposure, and becomes the main driver of risk and return. Using score-based tools to decide on allocation and risk-taking decisions thus leads to a misalignment of exposures with investor objectives, and unintended risk taking.

The consequence of this misalignment is that investors may end up with returns that fall short of their expectations. For example, the investor targeting the low investment tilt likely had a view that the factor would generate a positive premium while not expecting such a premium for the other factors, such as value. Figure 8 shows the performance impact of using the wrong factor measurement tools in allocation in the periods where value had poor performance, which was notably the case in the build-up to the 'technology bubble' (1998) and the period after it 'burst' (2002). The score-based approach to designing a low investment strategy resulted in a high value (HML) beta of 0.20 in 1998 and 0.23 in 2002, which would have led to an adverse performance impact of –4.8% and –2.4% respectively. Having a loss of 4.8% due to the poor performance of value is not what the investor expected to get out of choosing a low investment tilt! In addition, the unintended negative exposure to the low volatility factor would have piled on an additional –5.2% of poor performance in 2002. Overall, the factor-driven performance of this target score strategy would have been –5.8% and 4.4% in those periods.

We also compare this result to the result with the target beta strategy (which targets low investment beta of 0.75 and other factor betas of 0). The target beta strategy would have returned 3.1% and 16.1% respectively. Thus, investors suffer a shortfall of 8.9% and 11.8% in those two periods, which is due to the fact that they got the factor exposures wrong in their allocation. Recall that the target beta strategy is comparable to the target score strategy in that both strategies have the same long-term average score for the investment factor. Thus, the key difference between the two approaches is that one strategy controls factor exposures using scores while the other controls factor exposures using betas. The cost of using scores instead of beta is obvious from the results.

That the target score strategy suffers from losses in the value factor shows the consequence of mis-measuring factor exposures. If investors had chosen to be exposed to the value factor, facing losses when value does poorly is not likely to make them happy. However, when the investor has not even chosen to be exposed to value, suffering from value's losses will be a severe problem. In addition to the losses themselves, it would be extremely difficult to communicate these losses to stakeholders.

Of course, the analysis above considers short time periods of one year where the value factor has had exceptionally low returns. In times of 'normal' value returns, the performance impact of misaligned factor exposures will be lower. However, for risk management it is precisely the periods of unusual losses that matter.

An additional problem is that the one-dimensional nature of factor scores does not take correlations across different factors into account. This leads to double counting of factor exposures that are highly correlated. For example, we have shown that score-based analysis of a strategy that targets a constant beta to the low investment factor and zero beta to other factors leads to mismeasurement of the strategy's factor exposures. The pure investment tilt appears to have pronounced value (value beta of 0.32) and low volatility exposure (low volatility beta of 0.4) when considering scores. This is due to the positive correlation between the low investment, value and low volatility scores. The implication of this result is that investors who use score-based tools to analyse the performance of the pure investment strategy would

falsely believe that the strategy targets a mix of factors, leading to a misattribution of results.

Many popular factor scores combine variables into composite factor scores. Combining factor scores into composite scores makes the mismeasurement problems worse, as composites from skewed score distributions may be biased towards one of the variables. Above, we provided an example where one of the variables has an undue influence in determining high scores for the composite factor. We showed that a stock selection based on a quality composite score, which combines the high profitability and low investment scores, picks only 2% of stocks that score low on profitability, as opposed to 28% of stocks that score low on low investment. Thus, the resulting factor strategy will be biased towards the profitability dimension and implicitly underweight the low investment dimension. This dominance of profitability in the composite score is solely due to the technical properties of the score distribution. Investors who seek balanced exposure to each of the dimensions of quality will thus end up taking an implicit bet on the profitability dimension. We also show that lumping scores into a composite variable exacerbates the misidentification of the factor exposures underlying a strategy. For the pure investment tilt described above, the quality composite score can at times be significantly lower than its value score (0.53 vs 0.79 in March 1982) or its low volatility score (0.26 vs 0.81 in March 1997). Thus when using composite scores to analyse factor exposures, investors would misidentify the factors that are explicitly targeted by this strategy even more than when using the individual scores.

Given the fundamental flaw with the use of scores to measure 'exposures', as is done in numerous popular factor analytics toolkits, investors would benefit from considering beta-based exposures instead. A popular criticism faced by regression-based factor betas is the backward-looking nature of these exposures. However, this problem can be addressed by using best practices in beta estimation. For example, beta estimates can be improved by updating the betas based on the current composition of the portfolio instead of estimating the beta of a portfolio over a period where its composition is constantly changing. Moreover, to take into account the dynamic nature of factor betas, more sophisticated regression approaches can be employed, such as the use of exponential weighting, which puts more weight on more recent observations, or other approaches allowing time varying betas to be modelled explicitly.

Beta-based approaches offer the advantage that they do not suffer from mismeasurement problems that arise with score-based approaches due to factor correlations or skewed distribution. A key advantage of beta-based models is that they are aligned with the academic evidence on factor investing. Using such models can help investors take the correlation across factor returns into account and avoid unintended risk exposures due to mismeasurement issues with score-based approaches.

References

Asness, C. S., T. J. Moskowitz and L. H. Pedersen (2013). Value and Momentum Everywhere. *Journal of Finance* 68(3): 929–985.

Black, F., M.C. Jensen and M.S. Scholes (1972). The Capital Asset Pricing Model: Some Empirical Tests. Chapter in *Studies in the Theory of Capital Markets*, Praeger Publishers.

Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. *Journal of Finance* 52(1): 57–82.

Daniel, K., and S. Titman (1997). Evidence on the Characteristics of Cross Sectional Variation in Stock Returns. *Journal of Finance* 52(1): 1–33.

Fama, E. F., and K. R. French (1993). Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics* 33(1): 3–56.

Fama, E. F., and K. R. French (2015). A Five-Factor Asset Pricing Model. *Journal of Financial Economics* 116(1): 1–22.

Fama, E. F., and J. D. MacBeth (1973). Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy* 81(3): 607–636.

Harvey, C. R., Y. Liu and H. Zhu (2016). ... and the Cross-Section of Expected Returns. *Review of Financial Studies* 29(1): 5–68.

Lakonishok, J., A. Shleifer and R. W. Vishny (1994). Contrarian Investment, Extrapolation, and Risk. *Journal of Finance* 49(5): 1541–1578.

Lintner, J. (1965). Security Prices, Risk, and Maximal Gains from Diversification. *Journal of Finance* 20(4): 587–615.

Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. *Journal of Finance* 19(3): 425–442.

ERI Scientific Beta
1 George Street
#15-02
Singapore 049145
Tel: +65 6438 0030

EDHEC BUSINESS SCHOOL

Scientific Beta
An EDHEC-Risk Institute Venture

www.scientificbeta.com