Since November 23, 2009, EDHEC-Risk Institute has been designing equity smart beta indices.

With live annualised outperformance of 2.41%¹ for more than six years, these Smart Beta 1.0 indices based on the Efficient Maximum Sharpe Ratio methodology have shown that a good diversification method can lead to significant and robust outperformance over cap-weighted indices.

Since 2012, with the Smart Beta 2.0 framework, EDHEC-Risk Institute has created Scientific Beta Smart Factor Indices that are even better diversified and therefore more successful.

The Scientific Beta Smart Factor Indices for the rewarded long-term risk premia of Mid-Cap, Value, Momentum and Low Volatility have all produced positive annualised performance for all regions since they went live on December 21, 2012, with average annualised outperformance over the cap-weighted benchmark of 2.90%².

The Scientific Beta multi-smart-factor indices, which allocate to these four Smart Factor Indices, have a live track record that is even better than that of our Smart Beta 1.0 offering, with an annualised outperformance of 4.00% compared to their cap-weighted benchmark.³

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 at melanie.ruiz@scientificbeta.com

¹ - The average annualised outperformance of the FTSE EDHEC-Risk Efficient Index series (all regions) is 2.41% compared to its cap-weighted benchmark, computed using daily total returns from November 23, 2009 (live date) to December 31, 2015. The benchmark used is a cap-weighted portfolio of all stocks in the respective Scientific Beta universes.

² - Analysis is based on daily total returns from December 21, 2012 to December 31, 2015 for the USA, Eurozone, UK, Developed Europe ex UK, Japan, Developed Asia Pacific ex Japan, Developed Asia Pacific ex Japan, Developed ex UK, Developed ex US and Developed regions. The live date of the four Smart Factor Indices – Mid-Cap, Value, Momentum and Low Volatility – is December 21, 2012 for all regions. The benchmark used is a cap-weighted portfolio of all stocks in the respective Scientific Beta universes. The average outperformance for each factor across all regions is as follows: Mid-Cap (2.62%), Value (1.15%), Momentum (4.31%) and Low Volatility (3.50%), leading to an average across all four factors of 2.90%. All statistics are annualised. Source: scientificbeta.com.

³ - The average live outperformance across all Scientific Beta developed regions of Scientific Beta Multi-Beta Multi-Strategy (Equal Weight and Relative Equal Risk Contribution) indices is 4.00% and 3.77% respectively, while that of the Efficient Maximum Sharpe Ratio strategy in the same period is 2.86%. This live analysis is based on daily total returns in the period from December 20, 2013 (live date) to December 31, 2015, for the following developed world regions – USA, Eurozone, UK, Developed Europe ex UK, Japan, Developed Asia Pacific ex Japan, Developed ex UK, Developed ex US and Developed. The benchmark used is a cap-weighted portfolio of all stocks in the respective Scientific Beta universes.

Information containing any historical information, data or analysis should not be taken as an indication or guarantee of any future performance, analysis, forecast or prediction. Past performance does not guarantee future results.
INTRODUCTION

It is my pleasure to introduce the February 2016 edition of the EDHEC-Risk Institute “Research for Institutional Money Management” supplement in partnership with Pensions & Investments. Our aim with this supplement is to provide institutional investors with academic insights that are not only relevant, but also of practical use from a professional perspective.

We first look at the performance of smart factor indexes that are constructed based on combining a stock selection that targets a factor tilt with a diversified weighting scheme known as Diversified Multi-Strategy. We focus on assessments which take into account long-term evidence and on the performance observed after the commercial launch of the index. Every smart factor index outperforms the corresponding concentrated cap-weighted factor index over both the long term and the live period, providing very strong evidence of the robust benefits of diversification.

While there is a consensus on the existence of the value factor and the fact that it is rewarded over the long term, the implementation of value indexes, notably in the long-only universe, is not subject to the same consensus. Index construction mechanisms and various proprietary variable definitions and algorithms affect the return and risk properties of the resulting indexes and are different from provider to provider. Focusing solely on maximizing the value exposure may lead to concentration, which will result in greater unrewarded risk and wrong tilts to other rewarded risk factors, thus compromising the overall performance of the indexes. Investors should therefore not only prioritize selection of the right factor tilt but should also perform due diligence in comparing the different index providers and their offerings for the desired factor tilt in order to obtain the right factor tilt in an efficient way with robust performance.

Some argue that smart beta strategies are vulnerable to “crowding,” with increasing popularity posing a risk of overpricing and lower future returns. We find no evidence of this, but if one is concerned about potential crowding, the immediate concern should be to 1) hold well-diversified rather than concentrated strategies, and 2) spread out over many different strategies. Such an approach of avoiding concentration and diversifying across strategies is easy to implement with smart beta indexes.

We address the question of proprietary equity risk factor definitions and their deviation from the academic consensus on factor definitions. While providers refer to indexes resulting from such proprietary factor definitions as “enhanced” or “prime” factor indexes, one wonders whether such indexes might not also lead to an increased risk of data-snooping. Such data-snooping risk could mean that “enhanced” back-tested performance may not be repeatable out-of-sample.

We summarize recent research that was conducted with the support of Merrill Lynch Wealth Management in which we develop a general operational framework that can be used by financial advisors to allow individual investors to optimally allocate to categories of risks they face across all life stages and wealth segments so as to achieve personally meaningful financial goals. Individual investors do not need investment products with alleged superior performance; they need investment solutions that can help them meet their goals subject to prevailing dollar and risk budget constraints.

We would like to extend our warm thanks to our friends at P&I for their continuing commitment to the Research for Institutional Money Management supplement, which enables us to maintain our mission of bridging the gap between academic research and professional practice. We wish you an enjoyable and informative read.

INDEXES

4 Performance of Smart Factor Indexes: Long-Term and Live Track Records

10 A Flurry of Value Factor Indexes: Comparing the Performance of Different Approaches

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18 “Enhanced”, “Prime”, or just “Data-mined”? Over-fitting Risks in Factor Index Design

21 A Comprehensive Investment Framework for Goals-Based Wealth Management
This discussion of active managers’ sources of outperformance presents both live performance and long-term track records. This article covers the abovementioned principles and the performance of smart factor indexes.

Overview of factor indexes
Sophisticated institutional investors have increasingly started to review factor-based equity investment strategies. Ang, Goetzmann and Schaefer (2009) showed that the Norwegian Oil Fund’s actively managed portfolio can be justified by genuinely consensual academic research. Sophisticated institutional investors have increasingly turned to factor-based investment strategies in recent years, with the development of smart beta offerings, which make the same promises as asset managers, we have been seeing performance presentations that have fairly curious and lacking in credibility for three main reasons:

(i) Index providers choose, from their catalogue of indexes, the indexes that have performed best over the period for which they are presenting the performance.
(ii) Index providers come up with several methodologies for the same concept, or for the same representation of betas (see Exhibit 1). In the case where the methodology has not produced favorable live performance for a given smart beta, they have a notable tendency to replace it with a new methodology that has produced better results in-sample than the previous methodology produced over the live period.
(iii) Index providers produce multiple offerings on themes that are short term, in the sense that they are not justified by genuinely consensual academic research.

In response to this problem, Scientific Beta has taken care to:
- Have a consistent and unifying framework in the area of index construction, which means that all of its indexes follow the same conceptual approach.
- Have a limited flagship smart-factor offering and a flagship multi-smart-factor offering that is limited to 33 indexes that sum up the performance of its index platform and on which Scientific Beta communicates constantly.
- These flagship offerings correspond to smart-factor offers that are based on choices of factors and diversification methodologies that are well documented in the academic literature.
- Clearly distinguish between live performance and simulated performance. Producing long-term track records enables the performance and risks of the smart beta methodologies that are the object of indexes to be studied over the long run and the period is the same for all indexes.

This article covers the abovementioned principles and presents both live performance and long-term track records.

EXHIBIT 1
Factor indexes from various providers.
The vast majority of index providers focus only on identifying the right factor exposures and maximizing the factor exposures. In doing so, they create indexes that are heavily concentrated on a few stocks. Diversification is the only “free lunch” available in investment management and investors ignore diversification at their peril. Amenc et al. (2016) have shown that the benefits of well-diversified factor-tilted portfolios based on a broad selection of stocks and a diversified weighting scheme far outweigh those of a narrow selection of stocks with concentrated weighting schemes. Exhibits 3 and 4, taken from Amenc et al. (2016), summarize the performance and implementation costs of the concentrated and diversified factor-tilted indexes. Concentrating factor-tilted portfolios by moving from a broad selection to a narrow selection of stocks produces higher gross returns, but it also increases tracking error, resulting in at best marginal gains in risk-adjusted performance, before taking into account the costs of severely heightened turnover and reduced liquidity associated with narrower selections. On the other hand, using a well-diversified weighting scheme such as equal weighting leads to significant improvements in performance, with very few additional implementation costs. For a detailed analysis showing that well-diversified factor-tilted portfolios provide risk/return benefits as well as implementation advantages compared to highly concentrated approaches, we refer the reader to Amenc et al. (2016).

Amenc et al. (2014) addresses the problem of concentration in factor investing and enables investors to obtain the right rewarded risk exposures in an efficient and well-diversified way. The main idea is to apply a smart weighting scheme to an explicit selection of stocks that enables the construction of factor indexes that are not only exposed to the desired risk factors, but also avoid being exposed to unrewarded risks. This approach, referred to as “smart factor indexes,” can be summarized as follows. In a nutshell, the explicit selection of stocks provides the desired tilt, i.e., the beta, while the smart weighting scheme, known as Diversified Multi-Strategy, addresses concentration issues and diversifies away specific and unrewarded risks. All smart beta strategies are exposed to systematic risk factors and strategy-specific risks. The strategy-specific risks give rise to the lack of robustness of weighting schemes (see Amenc et al. 2015). The ERI Scientific Beta Diversified Multi-Strategy index combines, in equal proportions, the Efficient Maximum Sharpe Ratio, Efficient Minimum Volatility, Maximum Decentralization, Maximum Decorrelation and Diversified Risk Parity weighting schemes, thus diversifying away the strategy-specific risks associated with each individual weighting scheme. In this article, we assess the performance of the four smart factor indexes (Mid Cap, Momentum, Low Volatility and Value) that use the Diversified Multi-Strategy weighting scheme.

Most smart beta indexes are marketed on the basis of outperformance, but their back-tests are typically conducted over a limited time period, usually over 10 to 15 years. Assessing such back-tested performance over short periods does not allow significant conclusions to be drawn concerning the consistency of the performance of these strategies over time and the persistence of the outperformance beyond the back-test period. Therefore, discussing the performance of smart beta equity strategies over the long term and their performance over the live period is totally warranted. In this article, we look at both the long term (40-year period) and the look-back record performance of the four factor indexes that have the premium associated with the four risk factors — Size, Momentum, Low Volatility and Value.

Long-term performance

In this section, we assess the performance of the smart factor indexes over the 40-year time period from December 31, 1974 to December 31, 2014. Reliable stock-level data over such a long time period for the construction of smart factor indexes,” can be summarized as follows. In a nutshell, the explicit selection of stocks provides the desired tilt, i.e., the beta, while the smart weighting scheme, known as Diversified Multi-Strategy, addresses concentration issues and diversifies away specific and unrewarded risks. All smart beta strategies are exposed to systematic risk factors and strategy-specific risks. The strategy-specific risks give rise to the lack of robustness of weighting schemes (see Amenc et al. 2015). The ERI Scientific Beta Diversified Multi-Strategy index combines, in equal proportions, the Efficient Maximum Sharpe Ratio, Efficient Minimum Volatility, Maximum Decentralization, Maximum Decorrelation and Diversified Risk Parity weighting schemes, thus diversifying away the strategy-specific risks associated with each individual weighting scheme. In this article, we assess the performance of the four smart factor indexes (Mid Cap, Momentum, Low Volatility and Value) that use the Diversified Multi-Strategy weighting scheme.

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Long-term performance

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indexes is available only for the United States, so we limit our analysis to this country only.

We assess the performance of smart factor indexes for the four abovementioned factors published by Scientific Beta. These indexes select stocks based on their respective factor score and then employ a Diversified Multi-Strategy weighting scheme, which aims to obtain a diversified portfolio for a given stock selection.

Exhibit 5 summarizes the annual returns, relative returns and Sharpe ratio of the four smart factor indexes. Over the 40-year period under consideration, all four smart factor indexes have outperformed the cap-weighted benchmark. On average, the four smart factor indexes outperform the cap-weighted benchmark by 0.87% over the last 40 years. The risk-adjusted performance of the smart factor indexes is also significantly higher than that of the cap-weighted benchmark. The cap-weighted reference has a Sharpe ratio of 0.41, whereas the mid cap, momentum, low volatility and value smart factor indexes have Sharpe ratios of 0.70, 0.65, 0.70 and 0.71, respectively. On average, the four smart factor indexes have shown a 63% improvement in Sharpe ratio over the 40-year period. All four smart factor indexes outperformed the cap-weighted benchmark without much tracking error, so all four indexes have significant information ratios, ranging from 0.48 for the low-volatility index to 0.82 for the value index. On average, the four indexes have an information ratio of 0.69 over the 40-year period.

Robustness of performance

An advantage of long-term track records is that one cannot only analyze the average long-term performance but, given the long sample size, it becomes useful to look at a range of outcomes obtained during shorter sub-periods and various market conditions. Such an analysis provides an idea of how consistent the outperformance is in different periods or market conditions and provides a useful assessment of the robustness of the performance of the indexes. In this section, we look at a few robustness measures such as probability of outperformance, conditional performance analysis and short-term performance analysis for the smart factor indexes.

Probability of outperformance

The probability of outperformance is defined as the empirical frequency of outperforming the cap-weighted reference index over a given investment horizon. This measure is reported for investment horizons of three years by using a rolling window analysis with one-week step size. It is an intuitive measure to show how often the strategy has managed to outperform the cap-weighted reference index in the past, regardless of the entry point. Since smart beta strategies expose the investor to the risk of short-term underperformance relative to the cap-weighted benchmark, the frequency of underperformance becomes an important measure to evaluate the consistency of outperformance across time. It comes in handy to differentiate between two strategies which have similar long-term performance, although one of them has small but consistent outperformance while the other benefits from few periods of high gain combined with long periods of losses. It is calculated by computing the probability of obtaining positive excess returns if one invests in the strategy for a period of three years at any point during the complete history (in other words, after inception) of the strategy.

Exhibit 6 summarizes the probability of outperformance of the smart factor indexes over one-, three- and five-year rolling-window periods. It can be seen that all four smart factor indexes have a three-year outperformance probability of at least 70%, and on average the four indexes outperform the cap-weighted benchmark 78.07% of the time. It is also interesting to see how often all four indexes have outperformed the cap-weighted benchmark in the same time period, as opposed to each index outperforming the cap-weighted benchmark at different times. As shown in Exhibit 6, the four indexes together post a three-year outperformance probability of 66.51%. As the holding period increases to five years, the probability of outperformance increases further. On average, the smart factor indexes have a five-year outperformance probability of 86% and all four indexes together have outperformed 75.77% of the time over the same five-year period. The outperformance probability measures show that the smart factor indexes are robust even in shorter periods of analysis consistent with their long-term outperformance.

Overall, the analysis in this article generates interesting insights from both long-term and live track records.

2 The Diversified Multi-Strategy Weighting scheme is an equal-weighted combination of five different diversification weighting schemes, namely Maximum Deconcentration, Maximum Decorrelation, Efficient Minimum Volatility, Efficient Maximum Sharpe Ratio and Diversified Risk Weighting. Combining different weighting schemes within each weighting scheme. For a detailed overview of the construction methodology and the benefits of the Diversified Multi-Strategy Weighting scheme, please refer to Lodh and Sivasubramanian (2015) and Amenc et al. (2014).
Conditional performance

Analyzing the conditional performance of the smart beta strategies in bull/bear market conditions or in contraction/expansion business cycles is a powerful tool in robustness analysis because the performance of smart beta strategies is shown to vary over market phases (Goltz and Gonzalez (2015)). Bullish or bearish market conditions may have a considerable impact on how different portfolio strategies perform. Panel A in Exhibit 7 analyzes the relative performance of smart factor indexes in bull and bear markets. Positive market (broad CW) return quarters are classified as bull and negative market return quarters are classified as bear regimes. Panel B in Exhibit 7 analyzes the relative performance of smart factor indexes in extreme bull and extreme bear markets, i.e. the top 25% and bottom 25% markets. Out of 160 quarters analyzed, the 40 most bullish and 40 most bearish quarters are separated, defined by CW returns. It is worth noting that the different factor indexes perform differently in different market conditions. For example, the low volatility multi-strategy index performs well in bull markets (information ratio of 0.41), but poorly in bear markets (information ratio of 0.17). The mid-cap index, on the other hand, performs well in bull markets (information ratio of 0.94), but poorly in bear markets (information ratio of 0.43). Similar observations are seen in extreme market conditions as well.

Short-term performance

Further understanding of the performance of the factor indexes can be obtained by looking at their short-term performance. Exhibit 8 shows the calendar-year-wise relative returns of the four smart factor indexes and their average relative returns for the last 40 years. The performance of individual smart factor indexes is driven by the performance of the corresponding factor during the same period. As seen in Exhibit 8, there are remarkable differences in the performance of different factor indexes for a given year. It is also evident that the smart factor indexes outperform the cap-weighted benchmark in most years, except for the period from 1994 to 1999, marking the formation of the technology bubble which eventually burst in 2000. During the formation of the bubble, the cap-weighted benchmark outperformed the booming technology stocks compared to the smart factor strategies, which maintained effective diversification; therefore, during that period, smart factor indexes on average underperformed relative to the cap-weighted benchmark.

Live performance

Many investors consider that smart beta is often sold as a substitute for an active manager, so it seems relevant to look at the indexes’ live track records as well.

Live track record — performance analysis

Given that there are three full years of live track record available for the smart factor indexes, Exhibit 9 presents the performance of the four smart factor indexes over the three-year live period. All the single-factor indexes have positive excess return over the MSCI World Index and their average live annualized excess return is 1.81%. All four indexes exhibit significant risk-adjusted performance, as evidenced by their average information ratio of 0.68. In addition, their average Sharpe ratio shows a 31% improvement compared to the Sharpe ratio for MSCI World. The performance of the S& Pacific Developed Value Diversified Multi-Strategy Index is in line with the performance of MSCI World and actually slightly better, unlike most other value factor indexes in the market, which have seriously underperformed cap-weighted indexes in recent years. This positive relative performance is explained in large part by the good level of diversification of the specific and idiosyncratic risks of our smart factor indexes, while most other factor indexes are unfortunately overly concentrated and poorly diversified. These good live track records are also confirmation of the usefulness of taking into account the robustness criteria in the area of benchmark construction that are well known in the academic world.

Live track record — conditional performance analysis

Exhibit 10 shows the conditional performance of the smart factor indexes since their launch date. Panel A analyzes the relative performance of smart factor indexes in bull and bear markets. Positive market (broad CW) return quarters are classified as bull regimes and negative market return quarters are classified as bear regimes. Panel B analyzes the relative performance of smart factor indexes in extreme bull and bear markets, i.e. the top 25% and bottom 25% markets. Out of 160 quarters analyzed, the 40 most bullish and 40 most bearish quarters are separated, defined by CW returns. It is worth noting that the different factor indexes perform differently in different market conditions. For example, the low volatility multi-strategy index performs well in bull markets (information ratio of 0.41), but poorly in bear markets (information ratio of 0.17). The mid-cap index, on the other hand, performs well in bull markets (information ratio of 0.94), but poorly in bear markets (information ratio of 0.43). Similar observations are seen in extreme market conditions as well.
performance of smart factor indexes in extreme bull and bear markets — the 25% best bullish quarters and 25% worst bearish quarters. The performance observed is close to that produced in similar market conditions over the long term. The low volatility multi-strategy index performs very well in bear markets (information ratio of 0.93), but poorly in bull markets (information ratio of 0.43). The mid-cap index, on the other hand, performs well in bull markets (information ratio of 0.82), but poorly in bear markets (information ratio of 0.58). Similar observations can be made in extreme market conditions.

CONCLUSION

This article looks at the performance of smart factor indexes that are constructed based on combining a stock selection that targets a factor tilt with a diversified weighting scheme known as Diversified Multi-Strategy. The objective is to go beyond the common practice of assessing back-tested results over a 10- to 15-year period. Instead, we focus on assessments which take into account long-term evidence, or insights from both long-term and live track records.

The index construction approaches which build diversified portfolios for a given factor tilt yield greater performance benefits and are exposed to less unrewarded risk. It is possible to construct well-diversified, investible factor-tilted indexes without incurring excessive implementation costs. It is interesting to provide a summary of the benefits of such an approach by comparing these well-diversified factor indexes with more concentrated cap-weighted tilted indexes, which tilt to the same factors. Exhibit 11 provides a comparison of performance statistics over the long term and the live period between these two approaches. Every smart factor index outperforms the corresponding concentrated cap-weighted factor index over both the long term and the live period, providing very strong evidence of the robust benefits of diversification.

Overall, the analysis in this article generates interesting insights from both long-term and live track records.

Long-term track record analysis provides a detailed understanding of historical performance, including an analysis of robustness. Over a 40-year time period, all four smart factor indexes have outperformed the cap-weighted benchmark. The average outperformance probability for the four indexes, measured over a three-year horizon, is 78.07%. This shows that the smart factor indexes are robust even in shorter periods of analysis consistent with their long-term outperformance. The conditional performance analysis yielded further insight into the performance of the smart factor indexes in changing market conditions.

The live period performance of the assessed smart factor indexes is consistent with the long-term historical performance. All four smart factor indexes outperform the cap-weighted benchmark during the live period. The average live annualized excess return is 1.81% for the four indexes.

This double assessment of long-term and live performance provides evidence that the outperformance of the smart factor indexes analyzed in this article is not just present over a particular back-test period, but is robust for both long-term and live data.

References

Performance Comparison of Smart Factor Indexes and Cap-Weighted Factor Indexes.

**PANEL A – U.S. Long-Term Track Records**
The analysis period is from Dec. 31, 1974, to Dec. 31, 2014 (40 Years). Daily total return series in USD are used. The risk-free rate is the return on the three-month U.S. Treasury Bill and the benchmark is the cap-weighted reference of the 500 largest stocks in the United States.

<table>
<thead>
<tr>
<th></th>
<th>USA LTTR 31-Dec-1974 to 31-Dec-2014</th>
<th>Mid Cap</th>
<th>High Momentum</th>
<th>Low Volatility</th>
<th>Value</th>
<th>Average of 4 smart factor indexes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ann. Returns</td>
<td>12.16%</td>
<td>15.49%</td>
<td>16.75%</td>
<td>13.10%</td>
<td>15.65%</td>
<td>12.40%</td>
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<tr>
<td>Ann. Volatility</td>
<td>17.12%</td>
<td>17.59%</td>
<td>16.57%</td>
<td>17.30%</td>
<td>16.12%</td>
<td>15.50%</td>
</tr>
<tr>
<td>Sharpe Ratio</td>
<td>0.41</td>
<td>0.59</td>
<td>0.70</td>
<td>0.46</td>
<td>0.65</td>
<td>0.47</td>
</tr>
<tr>
<td>Ann. Excess Returns</td>
<td>-</td>
<td>3.33%</td>
<td>4.59%</td>
<td>0.94%</td>
<td>3.49%</td>
<td>0.24%</td>
</tr>
<tr>
<td>Ann. Tracking Error</td>
<td>-</td>
<td>5.75%</td>
<td>6.38%</td>
<td>3.50%</td>
<td>4.72%</td>
<td>4.47%</td>
</tr>
<tr>
<td>Information Ratio</td>
<td>-</td>
<td>0.58</td>
<td>0.72</td>
<td>0.27</td>
<td>0.74</td>
<td>0.05</td>
</tr>
</tbody>
</table>

**PANEL B – Developed World Live Track Records**
The analysis period is from Dec. 21, 2012 to Dec. 31, 2015. Daily total return series in USD are used. The risk-free rate is the return on the three-month U.S. Treasury Bill and the benchmark is the MSCI World Index. The live date of the SciBeta single-factor multi-strategy indexes is Dec. 21, 2012.

<table>
<thead>
<tr>
<th></th>
<th>Developed World 21-Dec-2012 to 31-Dec-2015</th>
<th>MSCI World</th>
<th>Mid Cap</th>
<th>High Momentum</th>
<th>Low Volatility</th>
<th>Value</th>
<th>Average of 4 smart factor indexes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ann. Returns</td>
<td>10.06%</td>
<td>11.45%</td>
<td>11.93%</td>
<td>11.57%</td>
<td>12.80%</td>
<td>10.23%</td>
<td>12.56%</td>
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<tr>
<td>Ann. Volatility</td>
<td>10.86%</td>
<td>10.82%</td>
<td>10.04%</td>
<td>11.04%</td>
<td>10.37%</td>
<td>9.76%</td>
<td>8.96%</td>
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<tr>
<td>Sharpe Ratio</td>
<td>0.92</td>
<td>1.05</td>
<td>1.18</td>
<td>1.04</td>
<td>1.23</td>
<td>1.04</td>
<td>1.40</td>
</tr>
<tr>
<td>Ann. Excess Returns</td>
<td>-</td>
<td>1.40%</td>
<td>1.87%</td>
<td>1.51%</td>
<td>2.74%</td>
<td>0.17%</td>
<td>2.50%</td>
</tr>
<tr>
<td>Ann. Tracking Error</td>
<td>-</td>
<td>2.40%</td>
<td>2.48%</td>
<td>2.01%</td>
<td>2.51%</td>
<td>2.18%</td>
<td>3.15%</td>
</tr>
<tr>
<td>Information Ratio</td>
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<td>0.75</td>
<td>0.75</td>
<td>1.09</td>
<td>0.08</td>
<td>0.79</td>
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</tbody>
</table>

This article covers the abovementioned principles and presents both live performance and long-term track records.
The value factor is one of the most consensual and widely documented equity factors. There is ample evidence and an array of theoretical explanations suggesting that tilting an equity portfolio toward low-valuation stocks allows above-market returns to be harvested. Given its long history, there is naturally a plethora of smart beta indexes that are targeted at harvesting the value premium.

While there is a consensus on the existence of the value factor and the fact that it is rewarded over the long term, it must be acknowledged that the implementation of value indexes, notably in the long-only universe, is not subject to the same consensus. While the primary objective of all those value-tilted indexes is to achieve positive exposure to the value factor, each index provider has a different construction mechanism in terms of factor definitions, weighting mechanisms and numerous implementation rules and constraints to make the indexes easily investable. These construction choices greatly alter the behavior of the indexes and their overall return and risk properties.

Exhibit 1 provides a brief summary of the methodologies of various value indexes available on the market. As can be seen from Exhibit 1, the most prominent difference that distinguishes the various commercial value indexes is the choice of the value proxy variable. The most consensual variable proxy definition available in the academic literature for the value factor is the book-to-market ratio. It is straightforward to benefit from the value premium by using the consensus variable definition from the academic literature. The advantage of such an approach is that the methodology and the back-tested performance are directly linked to a well-documented factor and are thus backed up by the empirical evidence and theoretical explanations for that factor.

However, many index providers use various proprietary definitions of the value factor, such as combinations of various accounting ratios, including the earnings yield, cash-flow yield, dividend yield, sales-to-price, etc. Moreover, some index providers may integrate additional criteria such as sales growth, use initial screens on items such as profitability, and run various adjustments to basic accounting measures such as adjusting for the leverage or sector group of a stock. Such adjustments may often introduce biases towards other risk factors, such as low volatility, that in turn may alter the performance of the indexes.

Importantly, there are several reasons why the use of such proprietary variables may lead to potentially severe disadvantages (see Amenc et al. (2016)). First of all, when moving from the standard value definition to proprietary tweaks, we cannot rely on post-publication evidence. In fact, while the standard value factor has survived for about 25 years after being published widely, we do not have evidence that proprietary tweaks have been effective out-of-sample. Moreover, while we have a sound theoretical explanation for why the standard book-to-market factor exists, there is little theoretical grounding for why another variable should do better than book-to-market. Moreover, such proprietary factor definitions increase the risk of data-snooping. A variable picked from an almost infinite number of possible ad hoc-tweaked factor definitions based on past performance is unlikely to perform the best in the future as well.

Many providers use a combination of several of the variables listed above and create a composite measure to evaluate

Exhibit 1: A Flurry of Value Factor Indexes: Comparing the Performance of Different Approaches

<table>
<thead>
<tr>
<th>Index Name</th>
<th>Factor Definition</th>
<th>Stock Selection</th>
<th>Weighting Scheme</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scientific Beta Value Multi-Strategy Index</td>
<td>Book-to-Market</td>
<td>50% of stocks in the universe based on factor score</td>
<td>Diversified Multi-Strategy</td>
</tr>
<tr>
<td>PTSE RAFI Developed</td>
<td>Composite of Sales, Cash Flow, Book Value and Dividends</td>
<td>Top 1,000 stocks ranked on composite score</td>
<td>Score Weighting</td>
</tr>
<tr>
<td>PTSE Developed Value Factor</td>
<td>Composite of Cash Flow Yield, Earnings Yield and Sales-to-Price</td>
<td>None</td>
<td>Composite score times</td>
</tr>
<tr>
<td>MSCI World Enhanced Value</td>
<td>Composite of Forward Price-to-Earnings, Price-to-Book and Enterprise Value-to-</td>
<td>Fixed number of securities based on flow algorithm with a target 30% cap coverage</td>
<td>Composite score times</td>
</tr>
<tr>
<td></td>
<td>Operating Cash Flow</td>
<td></td>
<td>Market Capitalization</td>
</tr>
<tr>
<td>MSCI World Value Weighted</td>
<td>Composite of Book Value, Sales Value, Earnings Value and Cash Earnings Values</td>
<td>None</td>
<td>Ratio of Composite Score and</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Market Cap</td>
</tr>
<tr>
<td>Russell Developed Value</td>
<td>Composite of Book-to-Price, 5 year IBES forecast and 5 year sales per share growth used to determine either value or growth probability</td>
<td>Stocks with pure value probability (100%) plus a percentage of the middle sector comprised of companies with both value and growth probabilities</td>
<td>Cap-Weighting</td>
</tr>
<tr>
<td>Russell Developed LC HE Value</td>
<td>Composite of Book-to-Price and Earnings-to-Price</td>
<td>None</td>
<td>Proprietary algorithm known as</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>NLP</td>
</tr>
<tr>
<td>S&amp;P Enhanced Value Developed LMC</td>
<td>Composite of Book-to-Price, Earnings-to-Price and Sales-to-Price</td>
<td>Generally 20% of the parent index constituents</td>
<td>Composite score times</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Market Capitalization</td>
</tr>
<tr>
<td>S&amp;P Intrinsic Value Weighted Developed</td>
<td>Book Value and Discounted Adjusted Earnings</td>
<td>None</td>
<td>Score Weighting</td>
</tr>
<tr>
<td>S&amp;P Developed EMHI Value</td>
<td>Composite of Book Value-to-Price, Cash Flow to Price, Dividend Yield and Sales-to-Price + three growth measures</td>
<td>33% of market cap with the highest value score plus some percentage of the blended basket of growth and value</td>
<td>Cap-Weighting</td>
</tr>
</tbody>
</table>

4 The Diversified Multi-Strategy Weighting Scheme is an equal-weighted combination of five different diversification weighting schemes, namely Maximum Deconcentration, Maximum Decorrelation, Efficient Minimum Volatility, Efficient Maximum Sharpe Ratio and Diversified Risk Weighting. Combining different weighting schemes diversifies away the strategy-specific risks associated with each weighting scheme. For a detailed overview of the construction methodology and the benefits of the Diversified Multi-Strategy Weighting scheme, please refer to Lodh and Sivasubramanian (2013) and Amenc et al. (2014).
that the bias from such over-fitting using a composite measure is severe, with good back-tested performance providing little indication of the likely out-of-sample performance. In addition to differences in variable definition, commercial risk indexes differ in terms of concentration levels. Some indexes aim to obtain particularly strong value exposure through a stock selection that is often restrictive, resulting in relatively few securities in the portfolio in terms of the nominal number of stocks. Moreover, the weighting scheme applied relatively few securities in the portfolio in terms of the nominal indication of the likely out-of-sample performance. Through a stock selection that is often restrictive, resulting in very uneven distribution of weights. Therefore, the effective number of stocks in the portfolio will also be low. The idea behind this concentrated value indexing approach is to maximize the return associated with the strongest value exposure possible over the long term. From a conceptual perspective, products that aim to capture explicit risk-factor tilts through concentrated portfolios effectively neglect adequate diversification. This is a serious issue because diversification has been described as the only “free lunch” in finance. Diversification allows a given exposure to be captured with the lowest level of total risk required, as it eliminates non-systematic risk. In contrast, taking on factor exposures such as a value tilt exposes investors to systematic risk factors. Rewards for doing so do not constitute a “free lunch,” but compensation for risk in the form of systematic factor exposures. Capturing risk premia associated with the value factor may be attractive for investors who can accept the value exposure in return for commensurate compensation. However, value-tilted strategies, when they are very concentrated, may also take on other, non-rewarded, risks. Non-rewarded risks come in the form of idiosyncratic (i.e., firm-level) risk, as well as other unrewarded risks (e.g., currency risk, sector risks and other unrewarded micro- or macro-economic factors). Financial theory does not provide any reason why such risk should be rewarded. Therefore, a sensible approach to value investing should not only look to obtain a value tilt, but also at achieving proper diversification within that factor tilt. From an empirical perspective, Amenc et al. (2016) have shown that the benefits of well-diversified factor-tilted portfolios based on a broad selection of stocks and a diversified weighting scheme far outweigh those of a narrow selection of stocks with concentrated weighting schemes. They show that concentrating factor-tilted portfolios by moving from a broad selection to a narrow selection of stocks produces higher gross returns, but it also increases volatility and tracking error, resulting in at best marginal gains in risk-adjusted performance before taking into account the costs of the severely heightened turnover and reduced liquidity associated with narrower selections. On the other hand, using a well-diversified weighting scheme such as equal weighting leads to significant improvements in performance, with marginal impact on turnover costs for a given level of stock selection. Hence, the authors argue that concentrated indexes are associated with high implementation costs without much improvement in performance, while at the other end of the spectrum, well-diversified indexes have pronounced improvement in performance with very few additional implementation costs. Finally, index providers often have to apply several proprietary rules and constraints, such as applying a turnover or liquidity cap or a cap on sector or country level exposure to improve the investability of the index. This might further increase the concentration of the indexes and alter their expected behavior. In the next section, we will analyze the performance of several commercially marketed value indexes and their factor exposures.

Performance of various value factor indexes

It can be seen that many value-tilted indexes do not outperform the cap-weighted benchmark over the 10-year sample period.

<table>
<thead>
<tr>
<th>Absolute Performance</th>
<th>Value Factor</th>
<th>Value Weighted</th>
<th>MSCI World</th>
<th>Relative Performance</th>
<th>Value Factor</th>
<th>Value Weighted</th>
<th>MSCI World</th>
</tr>
</thead>
<tbody>
<tr>
<td>SciBeta Developed</td>
<td>7.79%</td>
<td>7.80%</td>
<td>6.21%</td>
<td>7.57%</td>
<td>6.02%</td>
<td>5.94%</td>
<td>7.44%</td>
</tr>
<tr>
<td>SciBeta Enhanced</td>
<td>17.63%</td>
<td>18.63%</td>
<td>16.16%</td>
<td>20.07%</td>
<td>19.68%</td>
<td>18.67%</td>
<td>19.63%</td>
</tr>
<tr>
<td>Sharpe Ratio</td>
<td>0.37</td>
<td>0.29</td>
<td>0.25</td>
<td>0.31</td>
<td>0.25</td>
<td>0.25</td>
<td>0.32</td>
</tr>
<tr>
<td>Sortino ratio</td>
<td>0.50</td>
<td>0.40</td>
<td>0.35</td>
<td>0.43</td>
<td>0.34</td>
<td>0.34</td>
<td>0.44</td>
</tr>
<tr>
<td>Cornish-Fisher VaR</td>
<td>1.71%</td>
<td>1.84%</td>
<td>1.81%</td>
<td>1.92%</td>
<td>1.80%</td>
<td>1.77%</td>
<td>1.82%</td>
</tr>
<tr>
<td>Max DD</td>
<td>57.32%</td>
<td>61.06%</td>
<td>60.47%</td>
<td>61.67%</td>
<td>61.55%</td>
<td>61.02%</td>
<td>61.61%</td>
</tr>
<tr>
<td>SciBeta Developed</td>
<td>1.16%</td>
<td>0.37%</td>
<td>-0.42%</td>
<td>0.95%</td>
<td>-0.61%</td>
<td>-0.69%</td>
<td>0.81%</td>
</tr>
<tr>
<td>SciBeta Enhanced</td>
<td>2.42%</td>
<td>4.02%</td>
<td>3.55%</td>
<td>5.26%</td>
<td>2.72%</td>
<td>2.25%</td>
<td>3.90%</td>
</tr>
<tr>
<td>Information Ratio</td>
<td>0.48</td>
<td>0.09</td>
<td>-0.12</td>
<td>0.18</td>
<td>-0.22</td>
<td>-0.31</td>
<td>0.21</td>
</tr>
<tr>
<td>Outperformance probability Y1</td>
<td>70%</td>
<td>55%</td>
<td>43%</td>
<td>51%</td>
<td>45%</td>
<td>40%</td>
<td>55%</td>
</tr>
<tr>
<td>Outperformance probability Y2</td>
<td>74%</td>
<td>60%</td>
<td>11%</td>
<td>53%</td>
<td>10%</td>
<td>13%</td>
<td>49%</td>
</tr>
<tr>
<td>Outperformance probability Y3</td>
<td>100%</td>
<td>61%</td>
<td>18%</td>
<td>38%</td>
<td>13%</td>
<td>7%</td>
<td>81%</td>
</tr>
<tr>
<td>5% of Rolling 1-Y Rel. Returns</td>
<td>-3.58%</td>
<td>-4.98%</td>
<td>-4.43%</td>
<td>-8.15%</td>
<td>-4.53%</td>
<td>-4.88%</td>
<td>-4.66%</td>
</tr>
<tr>
<td>5% of Rolling 1-Y Tracking Error</td>
<td>4.19%</td>
<td>9.16%</td>
<td>7.80%</td>
<td>9.72%</td>
<td>5.59%</td>
<td>4.32%</td>
<td>8.91%</td>
</tr>
<tr>
<td>Cornish-Fisher Relative VaR</td>
<td>0.24%</td>
<td>0.31%</td>
<td>0.29%</td>
<td>0.53%</td>
<td>0.23%</td>
<td>0.20%</td>
<td>0.32%</td>
</tr>
<tr>
<td>Max Relative DD</td>
<td>5.68%</td>
<td>13.50%</td>
<td>12.04%</td>
<td>18.09%</td>
<td>11.51%</td>
<td>11.60%</td>
<td>12.24%</td>
</tr>
</tbody>
</table>
Interestingly, while most indexes rely on proprietary value definitions, the only index which follows a straightforward and consensual definition of the value factor is being identified by low book-to-market stocks actually produces the highest risk-adjusted return over the period. In fact, the SciBeta Developed Value smart factor index, which selects stocks based on book-to-market, not only outperforms the benchmark substantially but also outperforms every other competing index considered in terms of both returns and risk-adjusted measures such as Sharpe ratio and information ratio. Moreover, the SciBeta Value index avoids concentration and ensures a high level of diversification by being based on a broad stock selection of half the stocks in the reference universe and by applying a diversification-based weighting method to selected stocks. Owing to its construction philosophy, which is sharply focused on diversification, the index also has lower volatility and tracking error compared to the other value indexes. Besides such obvious benefits of a well-diversified index using a consensual variable, a point worth noting is the pronounced differences across value indexes, which have very similar labels but fare very differently over a 10-year sample period. In particular, it is worth noting that S&P’s “Enhanced Value” Index and MSCI’s “Enhanced Value” Index display a difference in annualized returns of almost 2%. Clearly, what is meant by “enhanced value” differs across implementations.

Exhibit 2 summarizes the absolute and relative risk and return performances of various competing value index offerings available in the Developed World universe. It can be seen that many value-tilted indexes do not outperform the cap-weighted benchmark over the 10-year sample period.

Factor exposures of value factor indexes

The primary purpose of a factor index is to achieve substantial exposure to the underlying factor to extract the corresponding factor’s risk premium. Exhibit 3 shows the factor exposures using five factor regression models for the various value-tilted indexes discussed in the previous section. As they are value-tilted indexes, it is natural to expect significant value factor exposure. As can be seen from Exhibit 3, while value exposures are generally positive as expected, some value-tilted indexes have very small or insignificant value tilts. This is the case for the sample period, for example, for the S&P Intrinsic Value Weighted Index. The fact that some indexes do not have strong positive exposure to the value factor is consistent with the fact that the methodologies do not rely on the consensus variable used in the definition of the standard value factor. For example, the S&P intrinsic value weighted index is constructed from proprietary measures of intrinsic value.

It is also worth noting that there are pronounced differences in the idiosyncratic risk measured by the standard deviation of residuals for the different value factor indexes. Idiosyncratic risk exposure, in fact, may arise from indexes deriving from the standard consensual factor definitions, leading their returns to be attributable not to the standard value risk factor, but to proprietary factors which are not included in standard value factor models such as the five-factor model. Another source of idiosyncratic risk is high concentration, which may lead index returns to be exposed to stock-specific risks, even if the variable for the factor definition was well aligned with the standard value definition. The annualized standard deviation of residuals below takes on particularly high values for the so-called “enhanced” value indexes (with idiosyncratic standard deviation of 3.38% and 5.41% annualized) which employ particularly exotic variable definitions that may be far removed from standard value and may lead to concentration, as well. It is perhaps not surprising that when one implements a concentrated portfolio of stocks that rank well on an exotic definition of “value,” one ends up taking idiosyncratic risk rather than gaining exposure to the well-known systematic risk factor for value risk.

CONCLUSION

Even though there are many indexes available on the market that claim to harvest the value risk premium, not all of them are the same. The index construction mechanisms and various proprietary variable definitions and algorithms affect the return and risk properties of the resulting indexes and are different from provider to provider. Focusing solely on maximizing the value exposure may lead to concentration, which will result in greater unrewarded risk and wrong tilts to other rewarded risk factors, thus compromising the overall performance of the indexes. Investors should therefore not only prioritize selection of the right factor tilt but should also perform due diligence in comparing the different index providers and their offerings for the desired factor tilt in order to obtain the right factor tilt in an efficient way with robust performance.

References


QUALITY INDICES

ERI Scientific Beta offers investors a series of Multi-Beta Multi-Strategy Quality indices. These indices provide access to the rewards associated with the Profitability and Investment factors, which are the subject of consensus in the academic world for defining the quality dimension in the equity universe.

Like all Scientific Beta indices, these indices benefit from robust diversification of their unrewarded specific risk and as such present risk-adjusted returns that are both highly attractive and without equivalent on the market.

Whatever the developed universe region considered, these indices have been outperforming their cap-weighted counterparts, delivering average annual outperformance of 3.46%.  

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

1 - The average annualised relative return since the base date compared to the cap-weighted benchmark for Scientific Beta Multi-Beta Multi-Strategy Quality indices for various regions as of January 22, 2016 is 3.46%. The base date is June 21, 2002. Analysis is based on daily total returns (with dividends reinvested) from June 21, 2002 to January 22, 2016 for the Developed, USA, Extended USA, Eurozone, UK, Extended Developed Europe, Japan, Developed Asia Pacific ex Japan, Developed ex USA, Developed ex UK, and Developed Europe ex UK regions. The benchmark used is a cap-weighted portfolio of all stocks in the respective Scientific Beta universes. All statistics are annualised. Source: scientificbeta.com.

Information containing any historical information, data or analysis should not be taken as an indication or guarantee of any future performance, analysis, forecast or prediction. Past performance does not guarantee future results.
Smart beta has been establishing a space in between traditional (cap-weighted) passive investments and traditional (proprietary and discretionary) active management. Smart beta draws fierce criticism from providers of both traditional active management and traditional passive management. Perhaps unsurprisingly, advocates of traditional active and passive management find that smart beta is not quite to their liking. In a nutshell, proponents of proprietary active strategies complain that smart beta is not active enough (see, for example, Yasenchak and Whitman (2015)) while proponents of traditional cap-weighting say that smart beta is not passive enough (see, for example, Philips et al. (2015)).

Among such critiques, a recurring issue is the presumption of a risk of “crowding” in smart beta strategies. For example, Jacobs (2015) argues that smart beta strategies are vulnerable to “crowding,” with increasing popularity posing a risk of overpricing and lower future returns. While crowding is commonly pointed to as a potential risk, it is rarely formalized or even defined. The main idea behind a crowding risk is that, as everyone knows about successful smart beta strategies and increasingly invests in them, flows into these strategies will ultimately cancel out their benefits. If an increasing amount of money starts chasing the returns to a momentum strategy, for example, it is possible that the reward for holding this strategy — which has been documented with historical data — will ultimately disappear.

Given that the most popular smart beta strategies already have a wide following, it should be feasible to establish evidence of the negative effects, if they exist, of being followed by increasing numbers of investors. It should be feasible to analyze whether popular smart beta indexes have led to over-crowding and come up with an empirical estimate of the magnitude of the drag associated with crowding that has occurred so far. As of today and to the best of our knowledge, there is no such evidence. But even when looking at the reasoning behind the supposed risk of crowding, one discovers several issues with the common wisdom about crowding.

### Risk-based explanations vs. mispricing

Whether or not we should expect crowding in smart beta strategies is closely related to the economic explanations of the premia we observe in the data. If factor premia are explained by a rational risk premium, the factor premium is likely to persist, because some investors will rationally avoid a tilt despite the higher returns. If, on the contrary, factor premia are due to systematic errors, and investors learn over time to correct these errors, factor strategies may indeed see diminishing premia, except if there are limits to arbitrage which mean that many investors will not be able to benefit from the premium. This issue has been discussed extensively in, e.g., Cochrane (1999). Proponents of the crowding argument claim that crowding will occur in standard factors and factor premia will diminish, but this will not be true if factors are explained rationally. More specifically, the table below shows explanations that are available in the literature for why factor premia may exist on standard factors. In fact, the existence of factor premia can be explained in two different ways — a risk-based explanation and a behavioral-bias explanation. The risk-based explanation premises that the risk premium is compensation to investors who are willing to take additional risk by being exposed to a particular factor. The behavioral explanation conceives that the factor premium exist because investors make systematic errors due to behavioral biases such as overreaction or under-reaction to news on a stock, leading to mispricing.

### Economic Explanations for Selected Factor Premia: Overview

<table>
<thead>
<tr>
<th>Indexes</th>
<th>Risk-Based Explanation</th>
<th>Behavioral Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
<td>Costly reversibility of assets in place leads to high sensitivity to economic shocks in bad times</td>
<td>Overreaction to bad news and extrapolation of the recent past leads to subsequent return reversal</td>
</tr>
<tr>
<td>Momentum</td>
<td>High-expected-growth firms are more sensitive to shocks to expected growth</td>
<td>Investor overconfidence and self-attribute bias leads to returns continuation in the short term</td>
</tr>
<tr>
<td>Low Risk</td>
<td>Liquidity-constrained investors hold leveraged positions in low-risk assets which they may have to sell in bad times when liquidity constraints become binding</td>
<td>Disagreement of investors about high-risk stocks leads to overpricing in the presence of short-sale constraints</td>
</tr>
<tr>
<td>Size</td>
<td>Low profitability leads to high distress risk and downside risk. Low liquidity and high cost of investment needs to be compensated by higher returns</td>
<td>Limited investor attention to smaller cap stocks</td>
</tr>
<tr>
<td>Profitability</td>
<td>Firms facing high cost of capital will focus on the most profitable projects for investments</td>
<td>Investors do not distinguish sufficiently between growth with high expected profitability and growth with low profitability, leading to underpricing of profitable growth firms</td>
</tr>
<tr>
<td>Investment</td>
<td>Low investment reflects firms’ limited scope for projects given high cost of capital</td>
<td>Investors undersell low investment firms due to expectation errors</td>
</tr>
</tbody>
</table>

---

smart beta strategies may be prone to “overvaluation, fragility and even factor crashes as investors withdraw on ma
once-popular but now underperforming factors” and asserts that “we’ve already seen an example in the collapse of mo
Give such claims, one can ask whether the losses in a particular factor at a particular point in time are indeed evi
-ment variation that one would expect in an “uncrowded” factor? If momentum losses are necessarily explained by crowding, how does one explain the momentum losses that occurred in the 1930s, for example? Was there crowding in momentum factor indexes in the 1930s? Likewise, if a loss in a factor is proof of “crowding,” one might as well claim that the equity market factor has experienced crashes, there must be over
crowding in the cap-weighted equity index. And when long-
term bonds severely underperform short-term bonds over a short period, is this then evidence of crowding by investors who are chasing the term premium?

In fact, claiming that there must be crowding in a factor because it suffers from losses completely ignores the nature of risk premia. A risk premium corresponds to a higher average return that is due to taking on additional risk. All risk fac
tors will have returns which vary substantially over time, and only an analysis of long-term data can lead to any meaningful conclusions on the average premium. We should note with Black (1990)10 that “we need decades of data for accurate es
timates of average expected return. We need such a long pe
riod to estimate the average that we have little hope of seeing changes in expected returns.” Thus, claiming that factor pre
mia have disappeared due to crowding based on short-term events is a risky business as far as the reliability of such conclusions is concerned.

Indeed, due to fluctuations in average returns, it is ex
pected that we will observe periods with low returns, and
given the uncertainty in estimating returns reliably, any sam
ple-specific conclusions should be handled with care. As an example, it is noteworthy that while the size factor is often claimed to have disappeared, and the value factor has been argued to be redundant based on sample-specific analysis, more general findings typically conclude that such factors are still relevant. For example, Fama and French (2015)11 concluded based on a U.S. sample that the value factor is redund
ant but Fama and French (2015b)12 do not find evidence of the redundancy of the value factor in global data and caution that tests on returns to value factor redundancy may be sample-spe
cific. Moreover, comprehensive comparisons of multi-factor models including different sets of factors show that factors such as value and size need to be included to successfully ex
plain the cross-section of expected returns (see Barillas and Shanken (2015)13).

In a nutshell, focusing on specific time periods is ill-suited to drawing inferences on the long-term behavior of factors. In fact, losses to any factor strategy over any particular period do not necessarily suggest that the long-term premium has disappeared because of “crowding” into a fashionable factor. Such losses may simply suggest that the reward for holding the factor comes with associated risk.

Where is the evidence?

While there is no specific evidence on the crowding ef
fects in particular smart beta indexes, a small number of re
cent studies examine potential effects of wide use of common factors for which a reward has been broadly documented.

While proponents sometimes cite such studies to sub
stantiate their claims about crowding risk, it should be em
phasized that recent studies do not provide clear evidence to suggest that factor premia are likely to disappear because of crowding. When inspecting the results in the unpublished working paper of Yost-Bremm (2014)14, which is sometimes cited in support of the crowding theory, one does not find conclusive evidence that crowding effects impose any meaningful cost on factor investors. Even though the paper finds evidence of abnormal trading volume for stocks which switch across thresholds of standard factor portfolios, the results do not necessarily imply a heavy burden or cost to strategies follow
ning standard factors. In fact, the evidence presented is strong for effects on trading volume but much weaker for effects on stock returns.

In fact, if one considers, for example, the effects around stocks that switch into the value portfolio, the results suggest the following. The study reports an effect on trading volume which is significant and consistent. Volume in switching stocks tends to increase consistently and in a statistically significant manner across the different model specifications the author tests. However, the return effect is not very consistent. Thus, while the volume effects are consistently shown as positive and significant for stocks switching to the value portfolio, re
turn effects are often insignificantly different from zero across the different model specifications, which is hardly strong evi
dence of an abnormal return phenomenon. Moreover, results in the paper show that a small percentage of firms actually switch into the value portfolio so that any abnormal returns of switching stocks only apply to a small fraction of assets held.

The overall effect on a value portfolio investor would be muted by the fact that most of the assets held are not switching stocks.

McLean and Pontiff (2015)15 address the question of whether the publication of results showing a return premium associated with an equity factor destroys this premium going forward. Specifically, they analyze the returns to almost 100 different strategies that tilt toward single or composite vari
ables, such as accounting variables or return-based variables. It should be noted that the study includes both consensual factors, such as those listed in the table above, and less stan
dard factors. Such non-standard factors are based on variables such as the firm age, corporate governance measures, inven
tory-related measures, seasonality, revenue surprises, changes in R&D spending, and analyst earnings forecasts.16 The authors analyze the in-sample result for a return premium over the pe
period used in the original study. They contrast this premium with the premium observed out-of-sample but before publication, and with the post-publication premium up to today.

If investors automatically “crowd” into factors once they know about the documented reward, one would expect the pre
mia to decline after publication of the respective paper. McLean and Pontiff attribute a 32% drop in returns to the publication effect. However, the authors also reject the hy
pothesis that post-publication anomaly returns decay en
tirely. The key conclusion is thus that while the publication of academic research tends to lower returns going forward, these premia do not disappear: It is noteworthy that this re
sult is obtained when analyzing a large number of almost 100
It should be emphasized that many smart beta strategies do not solely rely on tilting toward factors.

Factors, which include not only standard factors. As one increases the number of factors it may indeed be plausible that this may include all ad hoc factors with no clear economic rationale. Persistence of premia may arguably be even stronger when constraining the analysis to factors with a strong risk-based explanation. That the authors reject the hypothesis of crowding automatically cancels out factor returns for any systematic smart beta strategies.

Well-diversified factor indexes

It should be emphasized that many smart beta strategies do not solely rely on tilting toward factors. While many strategies labeled as “smart beta” effectively limit their strategy design to obtaining factor tilts, it should be noted that other strategies rely on diversification mechanisms to improve upon cap-weighted indexes. Even in the area of factor indexes, one can distinguish between two approaches, namely factor indexes which only deal with tilting towards stocks with favorable factor characteristics and well-diversified factor indexes, also termed smart factor indexes, which not only tilt to a given factor, but also ensure diversification through alternative weighting schemes.

Well-diversified or smart factor indexes implement the factor tilt through a stock selection, where stocks with above-average exposure for a given factor are retained. In a second step, these stocks are weighted by a combination of diversification-based methods which aim to create a well-balanced portfolio in terms of weights and risks. This weighting approach is referred to as Diversified Multi-Strategy weighting (see Amenc et al. (2014)\(^\text{11}\)). The idea behind this approach is to reconcile the exposure to the right factor with good diversification.

To illustrate the differences in terms of performance and risk, especially when the relevant factor underperforms, we provide results for the two different types of factor indexes for the value factor, which has suffered from relatively poor performance recently. The results in the table below compare a cap-weighted, and thus poorly diversified, value index, with a smart value index that uses the Diversified Multi-Strategy weighting scheme, looking at developed markets data over the past decade.

It appears from this example that using a diversification-based weighting scheme for the value stock selection has provided much better performance relative to the simple cap-weighted value-tilted portfolio in a time period when the returns to value were low. In fact, the multi-strategy value index led to positive outperformance over the broad cap-weighted index, while the cap-weighted value-tilted index led to underperformance. Moreover, the cap-weighted value-indexed index led to an increase in volatility relative to the broad cap-weighted index over this period, while the well-diversified multi-strategy index roughly matched the volatility of the broad cap-weighted index.

In a nutshell, a sensible approach to factor investing should not only look to obtain a factor tilt, but also at achieving proper diversification within that factor tilt. Interestingly, the importance of diversification for a given factor tilt was outlined more than 40 years ago in Benjamin Graham’s famous book on value investing “In the investor’s list of common stocks, there are bound to be some that prove disappointing. … But the diversified list itself, based on the above principles of selection […] should perform well enough across the years. At least, long experience tells us so.”\(^\text{12}\) Consistent with financial theory but also with the principles put forth by the early advocates of value investing, state-of-the-art smart beta index offerings focus not only on obtaining a factor tilt, but also on obtaining a well-diversified portfolio.

A practical answer to crowding concerns

While there is no convincing evidence to prove the crowding theories correct, thinking about the economic rationale behind a specific premium should provide ample answers to crowding concerns. If a factor return is explained by a risk-based rationale, there is no reason to expect crowding. For example, one may theorize that the well-documented long-term outperformance of equity index funds or long-term bonds over money market funds leads to crowding in the higher return funds. However, if such extra return is compensation for additional risk (i.e., the equity premium and the term spread), there is no reason why such premia should disappear even if they are known to investors. Therefore, potential smart beta investors should conduct thorough due diligence, not only on the past performance of a given strategy, but also on its economic rationale, and question whether a given reward can be expected to persist.

Moreover, precautions against crowding risks can be taken by proper implementation of factor investing and smart beta indexes. In particular, the best precaution against crowding seems to be diversification. If investors spread their smart beta investments across several strategies, and several factors, there should not be crowding in a single strategy. If any standalone strategy is well-diversified with weights spread out over a large number of stocks, such strategies should be less prone to potential crowding. Therefore, if one is concerned about potential crowding, the immediate concern should be to 1) hold well-diversified rather than concentrated strategies, and 2) spread out over many different strategies. Such an approach of avoiding concentration and diversifying across strategies is easy to implement with smart beta indexes, given the multitude of offerings available, and the different methodological choices across different indexes.

References


NOT ALL VALUE INDICES ARE EQUAL… SOME ARE SMART

Providers of smart beta indices that are exposed to the Value factor have been arguing for many years that their indices are not outperforming the market because the Value factor is underperforming cap-weighted indices.

While it is true that exposure to the Value factor has not been particularly rewarding over the past ten years, a Smart Factor Index, because it is well diversified, can add genuine value that allows investors to cope with this difficult environment for the factor.

With annual outperformance of 2.58% since the base date compared to MSCI World\(^1\) and annual live outperformance of 1.90% compared to MSCI World Value,\(^2\) the Scientific Beta Developed Value Diversified Multi-Strategy index is unquestionably a smart opportunity to invest in the Value factor.

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

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1 - The annualised relative return since the base date compared to MSCI World for the Scientific Beta Developed Value Diversified Multi-Strategy index as of December 31, 2015, is 2.58%. Analysis is based on daily total returns in USD from June 21, 2002 to December 31, 2015. The base date is December 21, 2002 for the Scientific Beta Developed Value Diversified Multi-Strategy index. MSCI World is used as the benchmark. All statistics are annualised.

2 - The annualised relative return since live date compared to MSCI World Value for the Scientific Beta Developed Value Diversified Multi-Strategy index as of December 31, 2015, is 1.90%. Analysis is based on daily total returns in USD from December 21, 2012 to December 31, 2015. The live date is December 21, 2012 for the Scientific Beta Developed Value Diversified Multi-Strategy index. MSCI World Value is used as the benchmark. All statistics are annualised.

Information containing any historical information, data or analysis should not be taken as an indication or guarantee of any future performance, analysis, forecast or prediction. Past performance does not guarantee future results.
INDEXES

“Enhanced”, “Prime”, or just “Data-mined”?
Over-fitting Risks in Factor Index Design

Felix Goltz
Head of Applied Research
EDHEC-Risk Institute
Research Director, ERI Scientific Beta

Factor index providers have come up with innovative proprietary factor definitions that deviate considerably from academic consensus on factor definitions. While providers refer to indexes resulting from such proprietary factor definitions as “enhanced” or “prime” factor indexes, an important question is whether such indexes do not also lead to an increased risk of data-snooping. Such data-snooping risk could mean that “enhanced” back-tested performance may not be repeatable out-of-sample.

Mismatch with academic factors

Academic studies of equity factors stick to a limited number of consensual and straightforward characteristics to identify factors. Index providers, on the other hand, have introduced a perplexingly vast set of ever more exotic proprietary factor definitions. More often than not, index providers not only introduce proprietary variables, but they also form composite factor scores by combining several such variables. The table below provides an overview of index provider definitions of factors and compares them to the standard academic factor composite factor scores by combining several such variables.

Selection bias

There is a strong risk of data-mining linked to the selection of proprietary factor definitions. Many providers use innovative variable definitions, adjustments and “enhancements.” Searching over many possible “enhanced factors,” one will find some definitions that show good back-tested performance purely by chance. Selecting the most successful factor definitions in the back-test is not likely to lead to repeatable results out-of-sample. Instead, selecting the best amongst a large set of possible factor definitions may unveil a “factor” that has no true premium and is simply the result of data-mining. Harvey and Liu (2015) refer to such factors as “lucky factors.” This selection bias will be higher when there is more flexibility in designing factors, and more variations are tried. In this context, the highly enhanced proprietary factors used by many product providers clearly provide for almost infinite possibilities of creating variations that look good in the back-test.

Over-fitting bias

Moreover, it is important to note that many providers rely heavily on composite factor scores. Novy-Mark (2015) argues that composite scoring approaches entail a much higher risk of data-snooping and biased back-test results than single-variable strategies. He shows that creating a composite variable based on the in-sample performance of single-variable strategies generates an over-fitting bias. To make matters worse, this over-fitting bias interacts with the general selection bias that even single-variable strategies may suffer from. The presence of both biases in composite variable smart beta strategies increases the data-mining problems exponentially. Novy-Mark finds that a back-test based on composite scoring using the “best k of n” variables is almost as biased as a back-test of a strategy where one selects the single variable that had the best performance of n to the power of k candidate variables. For example, using a composite score where one selects three variables out of six candidate variables is as biased as selecting, with hindsight, a single variable from 729 (3 to the power of 6) candidate variables. Likewise, selecting a composite of five variables out of 10 based on back-tested performance is almost as bad as selecting a single variable among roughly 10 million (5 to the power of 10) candidate variables. This result underlines that the use of composite scores may lead to a severe data-snooping bias. As the author concludes, “combining spurious, marginal signals, it is easy to generate back-tested performance that looks impressive.”

Inconsistencies

Data-mining risks are exacerbated by inconsistencies across time and across the product range. Indeed, some providers employ a multitude of parallel indexes using different definitions for the same factor (e.g., “value”). Perhaps more strikingly, some providers do not hesitate to introduce new indexes with definitions that are at odds with their earlier factor index offerings. This implies that such providers change their mind quite often on what a good proxy for a given factor is.

Overview of index provider factor definitions.

<table>
<thead>
<tr>
<th>Provider</th>
<th>Value</th>
<th>Momentum</th>
<th>Quality</th>
</tr>
</thead>
<tbody>
<tr>
<td>Goldman Sachs Equity Factor Index World</td>
<td>Value score from proprietary risk model (Alphas), relative to stock’s regional industry group</td>
<td>Residuals from cross-sectional regression of 12-month return (omitting last month) on stock volatility</td>
<td>Composite based on asset turnover, liquidity, ROA, operating CP to asset ratios, accruals, gross margin, leverage</td>
</tr>
<tr>
<td>MSCI Multi-Factor Indexes (2013)</td>
<td>Sector-relative composite factor based on Enterprise Value / Operating CF, Forward P/E, Price-to-Book</td>
<td>Composite score based on excess return divided by ann. volatility over past 12 months and and past 6 months</td>
<td>Composite based on operating CF to debt, net income to assets, annual change in (sales over assets), accruals</td>
</tr>
<tr>
<td>FTSE Global Factor Index Series</td>
<td>Composite based on Cash Flow-to-Price, Net Income-to-Price, and Country-Relative Sales-to-Price</td>
<td>Mean/Sd. dev. of “avg. residual” from 11 rolling window regressions of past 36 months’ returns on country and industry index</td>
<td>Composite based on operating CF to debt, net income to assets, annual change in (sales over assets), accruals</td>
</tr>
<tr>
<td>Deutsche Bank Equity Factor Indexes</td>
<td>Composite based on inverse of Enterprise Value to EBITDA and dividend yield</td>
<td>Past 12-month return (omitting last month) minus risk adjustment times idiosyncratic volatility score</td>
<td>Composite based on return on invested capital and net operating assets growth</td>
</tr>
</tbody>
</table>

It should be unsurprising if a newly re-engineered version of a given factor tilt has back-tests that look better over the recent period than the live performance of older indexes. In fact, since one has an almost unlimited range of variations that one can test when introducing changes in factor definitions and ad hoc adjustments, it should be quite manageable for a provider to create new versions of a factor-titled index that yields in-sample performance that is far more alluring than that of a previous offering, particularly when the former’s simulated performance is compared to the latter’s live performance.

The key issue is that proprietary “tweaks,” without any constraint of consistency, increase the number of possible variations a provider can test. Using a simple consensual indicator for a factor guards against such post-hoc variable picking. Moreover, providers would be well advised to employ “some kind of framework to limit the number of possibilities that we search over” (Lo [1994]). When making index design decisions within a consistent framework, the risks of over-fitting index design to match patterns in past data is effectively controlled.

It is indeed regrettable that providers of indexes do not pay more attention to consistency when it comes to factor definitions. Indeed, providers of cap-weighted indexes pride themselves for consistency in their cap-weighted index offering, and mention consistency as a key benefit of their indexes within a consistent framework, the risks of over-fitting index definitions a provider can test. Using a simple consensual indicator for a factor guards against such post-hoc variable picking. Moreover, providers would be well advised to employ “some kind of framework to limit the number of possibilities that we search over” (Lo [1994]). When making index design decisions within a consistent framework, the risks of over-fitting index design to match patterns in past data is effectively controlled.

As an example of inconsistent factor definitions, Exhibit 2 shows the contrasting factor definitions used for implementing a multi-factor approach of a major index provider as described by the provider in 2013 and 2015. It is clear from the table that within a span of two years, how a factor is defined changes in a pronounced manner.

More often than not, inconsistencies over time may be driven by disappo inting live performance of previous offerings. As an illustration of the case where a newly launched index with a methodology which is inconsistent with the previous index leads to better back-tested performance than the live performance shown by the previous index, we provide below a comparison of two value indexes launched subsequently by the same provider. The results suggest that the back-tested performance of the new index as of its launch was able to improve considerably on the performance of the pre-existing index for the same factor. Thus, before its launch, the new Value index proposed by MSCI (Enhanced Value) considerably outperformed the live performance of the old Value index proposed by MSCI (Value Weighted).

EXHIBIT 2

<table>
<thead>
<tr>
<th>Scoring</th>
<th>2013</th>
<th>2015</th>
<th>Adjustments</th>
<th>2013</th>
<th>2015</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quality</td>
<td>Return on Equity, Debt-to-Equity and Earnings Variability. Average of z-score for each variable.</td>
<td>Return on Equity, Debt-to-Equity and Earnings Variability. Average of z-score for each variable.</td>
<td>No sector control. Sector-relative scoring.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Size</td>
<td>None: equal-weighting of large/mid cap stocks is prescribed as a way to capture the size premium.</td>
<td>Negative of the exposure from the Proprietary Equity Model: model uses a z-score based on the logarithm of the market cap of the relevant firm.</td>
<td>No country or sector control. Country control (the Proprietary model's descriptor is on a country-relative basis).</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Momentum</td>
<td>12-month and six-month local price performance. Simple average of z-scores.</td>
<td>Exposure from the Proprietary Equity Model based on 12-month relative strength (25% weight), six-month relative strength (37.5% weight), historical alpha (37.5% weight). Weighted sum of z-scores.</td>
<td>Momentum score is risk-adjusted. No explicit risk adjustment (use of Proprietary Model exposure).</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

EXHIBIT 3

<table>
<thead>
<tr>
<th>Developed Markets</th>
<th>1Y prior to launch of new index (08/11/2013-08/11/2014)</th>
<th>1Y prior to launch of new index (08/11/2013-08/11/2014)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSCI World Value Weighted (old index)</td>
<td>MSCI World Value Enhanced Value (new index)</td>
<td>MSCI World Value Weighted (old index)</td>
</tr>
<tr>
<td>Annualized Return</td>
<td>13.92%</td>
<td>17.32%</td>
</tr>
<tr>
<td>Annualized Volatility</td>
<td>9.87%</td>
<td>10.75%</td>
</tr>
<tr>
<td>Sharpe Ratio</td>
<td>1.41</td>
<td>1.61</td>
</tr>
<tr>
<td>Excess Return</td>
<td>-0.28%</td>
<td>3.11%</td>
</tr>
<tr>
<td>Tracking Error</td>
<td>1.37%</td>
<td>3.06%</td>
</tr>
<tr>
<td>Information Ratio</td>
<td>-0.21</td>
<td>1.02</td>
</tr>
</tbody>
</table>

Robustness through parsimony

Scientific Beta, with its factor-index methodology, has chosen an alternative to proprietary factor definitions. This choice is driven by the desire to avoid data-mining risks, and make sure that back-tested index performance provides an unbiased expectation on future long-term index performance. In fact, all Scientific Beta factor indexes use simple and parsimonious factor definitions which adhere to the variable definitions used in the academic literature. The table below provides an overview of the evidence on these and an overview of results obtained on key factors with long-term U.S. data.

Implications for due diligence

An important consideration with any smart beta index is the general risk of data-snooping. Given that any analysis of performance and risk of such recently launched indexes will mainly focus on back-tested data, a key question is how likely it is that the properties observed in the back-test carry over to future performance. The risk of data-snooping is heightened when providers use inconsistent ad hoc methodologies which allow an almost infinite number of index design variations to be tested in the back-test with the potential to then select the best performing index with hindsight. Since the results of such a selection process will heavily rely on sample-specific noise, it is not reasonable to expect that performance will be robust going forward. In this respect, when index providers change index methodologies and

23 Refer to 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.
More often than not, inconsistencies over time may be driven by disappointing live performance of previous offerings.

launch new or “enhanced” indexes for the same factor, or use different factor definitions across time for their multi-factor indexes, this should be a cause for concern for investors. Moreover, the fact that tweaked multi-variate proprietary factor definitions are used increases the risk of data-mining.

Adding a lot of bells and whistles to factor definitions may lead to over-fitting. If we tweak factor definitions extensively to obtain attractive back-tested performance, it becomes unlikely that the strategy will reproduce the results that were obtained under the specifics of the dataset used in the back-test. Sticking to simple standard factors instead aims at parsimony. Parsimony refers to the idea that one is able to explain “a lot” with “a little.” Parsimonious factors have a higher likelihood of capturing persistent effects rather than merely portraying sample-specific patterns. The statistician George E. P. Box famously argued in favor of parsimony by writing that “over-elongation and over-parameterization is often the mark of mediocrity.”

What is more, while we have more than 20 years of post-publication out-of-sample evidence on standard factors such as standard Value (based on book-to-market), Size (based on market capitalization) or Momentum (based on unadjusted absolute returns), the performance of enhanced proprietary factors cannot be analyzed over meaningfully long out-of-sample or post-publication periods.

Overall, a key challenge for such proprietary factor indexes is thus to convincingly document why performance should be expected to be not only “enhanced” in the back-tests, but also robust and achievable going forward. In the absence of such documentation, investors may be well advised to beware of data-mining risks and stick to consensual factors implemented within a consistent framework.

EXHIBIT 4
US Evidence on Equity Factor Premia.

<table>
<thead>
<tr>
<th>Factor</th>
<th>Factor Definition</th>
<th>Period</th>
<th>Premium</th>
<th>t-stat</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market</td>
<td>Excess returns of cap-weighted equity index</td>
<td>1926-2008</td>
<td>7.72% (annual)</td>
<td>3.47</td>
<td>Ang et al. (2009)</td>
</tr>
<tr>
<td>Low Risk</td>
<td>Stocks with low vs. high risk (beta, volatility or idiosyncratic volatility)</td>
<td>1926-2012</td>
<td>6.70% (monthly)</td>
<td>7.12</td>
<td>Frazzini-Pedersen (2014)</td>
</tr>
<tr>
<td>Size</td>
<td>Stocks with low vs. high market cap</td>
<td>1926-2006</td>
<td>2.28% (annual)</td>
<td>1.62</td>
<td>Ang et al. (2009)</td>
</tr>
<tr>
<td>Value</td>
<td>Stocks with high vs. low book-to-market</td>
<td>1926-2008</td>
<td>6.87% (annual)</td>
<td>3.27</td>
<td>Ang et al. (2009)</td>
</tr>
<tr>
<td>Momentum</td>
<td>Stocks with high vs. low returns over past 12 months (omitting last month)</td>
<td>1926-2008</td>
<td>9.34% (annual)</td>
<td>5.71</td>
<td>Ang et al. (2009)</td>
</tr>
<tr>
<td>Profitability</td>
<td>Stocks with high vs. low profitability (e.g. return on equity or gross profitability)</td>
<td>1963-2013</td>
<td>0.17% (monthly)</td>
<td>2.79</td>
<td>Fama-French (2014)</td>
</tr>
<tr>
<td>Investment</td>
<td>Stocks with low vs. high investment (change in total assets)</td>
<td>1963-2013</td>
<td>0.22% (monthly)</td>
<td>3.72</td>
<td>Fama-French (2014)</td>
</tr>
</tbody>
</table>

EXHIBIT 5
Live Performance (12/21/2012 to 09/30/2015) of Developed World Indexes.
The analysis is based on the weekly total returns dividends reinvested series in USD. The Developed Universe contains around 2,000 stocks. All statistics are annualized. Yield on Secondary U. S. Treasury Bills (3M) is used as a proxy for the risk-free rate. The MSCI World is used as the benchmark. The single-factor indexes considered here went live on 12/21/2012.

<table>
<thead>
<tr>
<th>Developed World</th>
<th>MSCI World</th>
<th>Scientific Beta Diversified Multi-Sharpe Ratios</th>
<th>Average of the 4 Smart Factor Indexes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Absolute Performance</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Annual Returns</td>
<td>8.86%</td>
<td>11.19%</td>
<td>11.19%</td>
</tr>
<tr>
<td>Volatility</td>
<td>11.69%</td>
<td>10.23%</td>
<td>10.71%</td>
</tr>
<tr>
<td>Sharpe Ratio</td>
<td>0.80</td>
<td>1.09</td>
<td>0.89</td>
</tr>
<tr>
<td>Relative Performance</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Annual Relative Returns</td>
<td>-</td>
<td>2.32%</td>
<td>2.73%</td>
</tr>
<tr>
<td>Tracking Error</td>
<td>-</td>
<td>2.61%</td>
<td>1.93%</td>
</tr>
<tr>
<td>Information Ratio</td>
<td>-</td>
<td>0.89</td>
<td>0.76%</td>
</tr>
</tbody>
</table>

References
MSCI, Deploying Multi-Factor Index Allocations in Institutional Portfolios, Research Insight, December 2013
MSCI, The MSCI Diversified Multi-Factor Indexes - Maximizing Factor Exposure While Controlling Volatility, Research Insight, May 2013
A Comprehensive Investment Framework
for Goals-Based Wealth Management

Individual investors do not need investment products with alleged superior performance; they need investment solutions

From a product-centric to an investor-centric approach to wealth management

Individual investors’ investment problems can be broadly summarized as a combination of various wealth and/or consumption goals, subject to a set of dollar budgets defined in terms of initial wealth and future income, as well as risk budgets such as maximum drawdown limits, for example.

The starting point of an investor-centric goals-based investment (GBI) approach consists of recognizing that the success or failure of these goals subject to dollar and risk budgets does not critically depend upon the standalone performance of a particular fund, nor that of a given asset class. It depends instead upon how well the investor’s portfolio dynamically interacts with the risk factors impacting the present value of the investor’s goals as well as the present value of non-tradable assets and future income streams, if any. In this context, the key challenge for financial advisors is to implement dedicated investment solutions aiming to generate the highest possible probability of achieving investors’ goals, and a reasonably low concentrated risk exposures — for example, under the form of illiquid asset allocations.

The focus of recent research that we conducted with the support of Merrill Lynch Wealth Management was to develop a general operational framework that can be used by financial advisors to allow individual investors to optimally allocate to categories of risks they face across all life stages and wealth segments so as to achieve personally meaningful financial goals.

One key feature in developing the risk allocation framework for goals-based wealth management is the introduction of systematic rule-based multi-period portfolio construction methodologies, which is a required element given that risks and goals typically persist across multiple time frames. Academic research has shown that an efficient use of the three forms of risk management (diversification, hedging and insurance) is required to develop an investment solution framework dedicated to allowing investors to maximize the probabilities of reaching their meaningful goals given their dollar and risk budgets. As a result, the main focus of the framework is on the efficient management of rewarded risk exposures.

The framework should not only be thought of as a financial engineering device for generating meaningful investment solutions with respect to investors’ needs. It should also, and perhaps even more importantly, encompass a process dedicated to facilitating a meaningful dialogue with the investor. In this context, the reporting dimension of the framework should focus on updated probabilities of achieving goals and associated expected shortfalls, as opposed to solely focusing on standard risk and return indicators, which are mostly irrelevant in this context.

Broadly speaking, GBI strategies aim to secure investors’ most important goals (labeled as “essential” — see definition below), while also delivering a reasonably high chance of success for achieving other goals, including ambitious ones which cannot be fully funded together with the most essential ones (and which are referred to as “aspirational”). Holding a leverage-constrained exposure to a well-diversified performance-seeking portfolio (PSP) often leads to modest probabilities of achieving such ambitious goals, and individual investors may increase their chances of meeting these goals by holding aspirational assets which generally contain illiquid assets such as private equity. In such a dynamic context, the framework involves a number of objective and subjective inputs, as well as a number of building-block and asset allocation outputs, all of which are articulated within a five-step process.

1. Objective inputs — realistic description of market uncertainty

The implementation of the framework requires the use of updated market data (for example, yield curve data), as well as the introduction of a Monte-Carlo simulation model, which is needed for the estimation of the probabilities of achieving investors’ goals. Constructing a Monte-Carlo simulation model involves realistic stochastic processes as well as a dynamically calibrated set of parameter values that are chosen so as to minimize the model pricing errors — that is, the distance between market prices and model-implied prices for a set of reference instruments. Goals-based investing strategies are based on observable quantities, and their implementation is therefore not subject to model or parameter risk. The specifications of a model, and the associated parameter values, are only needed to compute probabilities to achieve various goals, which is an important ingredient in the dialogue with private investors.

2. Subjective inputs — detailed description of investor situation

The implementation of the framework requires a number of inputs from the investor, including on the one hand
the investor’s existing assets and liabilities, as well as an esti-
mate of future consumption and revenue streams, and on the
other hand a list of the goals that should be inte-
grated in the wealth management process. Investors’ goals
can be classified into three groups: 1) essential goals (EG),
which are affordable and secured goals, 2) important goals
(IG), which are affordable but non-secured goals27, and 3) as-
pirational goals (AG), which are non-affordable (and non-se-
cured) goals28.

If a goal originally perceived as essential by an investor
is not affordable (or generally, if securing it involves too
high an opportunity cost), the investor is invited to secure a
lower level of consumption or wealth. The classification of
goals is intrinsically subject to interactions between the investor
and the financial advisor. This interaction is needed to allow
the investor to measure affordable goals against non-affordable
ones, and what the opportunity costs associated with securing
affordable goals are. This interaction also involves periodic
(say, annual) revisions. Indeed, the fundable status of the goal
(i.e., its affordability or non-affordability) depends on the pres-
ent value of the goal, thus on market conditions and notably
on interest rates, and the investor’s current wealth as well as future income. Moreover, the investor’s priorities may vary over
time.

3. Building-block outputs — goal-hedging and
performance-seeking portfolios

The first output of the framework consists in designing a
goal-hedging portfolio for each essential goal. The general
objective assigned to this portfolio is to secure the
goal with certainty, and to do so at the cheapest cost. Its exact
nature depends on the type of goal under consideration. In
the simple case of a consumption-based goal, for example,
the GHP is a dedicated bond portfolio (a real bond portfolio if
considering inflation-linked with coupon payments matching the
consumption cash-flows or as a first order approximation) with
duration matching the duration of the goal cash-flows. For more complex goals, such as multi-
period wealth goals in the presence of income streams,
the GHP can be a dedicated portfolio of exchange options,
which can be replicated accurately or approximately through
a suitable dynamic portfolio strategy29.

In addition to financing hedging portfolios associated
with all essential goals, the investor also needs to generate
performance so as to reach important and aspirational goals
with a non-zero probability. In this context, investors should
allocate some fraction of their assets to a well-diversified PSP
in an attempt to harvest risk premia on risky assets across fi-
nancial markets. An efficient GBI process will focus on utilizing
low-cost access to rewarded risk factors (beta exposures) to
achieve this objective. A consensus is emerging regarding
the inadequacy of market cap-weighted indexes as investment
benchmarks, and a new paradigm known as smart beta in-
vesting is emerging, starting from the equity space, with a
focus on the efficient harvesting of multiple risk premia in the
equity universe. These smart beta benchmarks blur the tradi-
tional clear-cut split between active vs. passive portfolios (see
Amenc et al. (2014) and offer a set of cost-efficient and at-
tractive investment vehicles in wealth management.

4. Asset allocation outputs — dynamic split between risky
and safe building blocks

One natural benchmark strategy consists in securing all
essential goals with (and indeed, the available liquid wealth in
one or several) performance portfolios allowing for the most
efficient harvesting of market risk premia. This strategy, which
is appealing since it secures essential goals with probability 1
and generates some upside potential required for the achieve-
ment of important and aspirational goals, is in fact a special
case of a wider class of (in general) dynamic GBI strategies.
These strategies advocate that the allocation to the
PSPs vs. GHPs should be taken as some function of the cur-
rent wealth level and the present value of the fraction of es-
sential goals that is financed by future cash inflows, with
the key property that this function (whose parameters in gen-
eral depend on market conditions) should converge to zero
when wealth converges to levels required for securing essen-
tial goals. (This condition can be regarded as a necessary and
sufficient condition for ensuring the protection of essential
goals with probability 1.)

The simplest example of a dynamic strategy satisfying
this property is one that takes the investment in the PSP equal
to a multiple of the margin for error (corresponding to the
function being taken as a linear function), with a unit multiplier
value leading to the benchmark buy-and-hold strategy. In im-
plementation, the multiplier is taken as a suitable function of
market conditions, thus allowing the opportunity cost of
downside protection to be decreased by activating the insur-
ance component only when most needed.

This class of strategies, which are reminiscent of constant
proportion portfolio insurance strategies extended to an in-
tegrated goals-based wealth management process, can be
shown to be optimal in the sense that they are the solution
to an expected utility maximization problem with (implicit)
goals for a leverage-constrained myopic investor. Such base
case strategies have to be further extended to encompass a
number of practically important dimensions, including the
presence of taxes or multiple essential goals, including those
that potentially apply to different wealth processes.

5. Reporting outputs — updated probabilities of reaching
goals

The framework is meant to be used both for generating
meaningful portfolio advice as well as for facilitating the dia-
logue with the investors, and provides a set of subjective out-
puts (probability of reaching goals and associated expected
shortfall) as well as objective outputs (allocation recommen-
dations at all points in time). From an operational standpoint,
it is likely more effective to have two separate processes,
each supported by distinct IT tools—an asset-liability manage-
ment tool meant to facilitate the relationship with the investor
and the associated reporting requirements, and an asset man-
agement tool dedicated to the execution of portfolio recom-
endations.

For a given allocation strategy (e.g., a fixed-mix rebal-
ancing toward the investor’s current allocation or a more com-
plicated and more optimal GBI strategy), a number of indicators
are reported, including the success probability for a strategy
to achieve any particular goal as well as the associated ex-
pected shortfall.

Paradigm changes in wealth management

The wealth management industry is about to experience a
profound paradigm change. It is expected that the next
generation of financial advisors will focus on building a mod-
ern approach to wealth management that will depart from a
product-centric search for performance to focus on satisfying
the clients’ needs through a dedicated investor-centric goals-
based investment solution approach (Ellis (2014)).

Any investment process should start with a thorough un-
derstanding of the investor problem. Individual investors do
not need investment products with alleged superior perform-
ance; they need investment solutions that could help them
meet their goals subject to prevailing dollar and risk budget
constraints.

Our research introduces a general operational frame-
work, which formalizes the goals-based risk allocation ap-
proach to wealth management proposed in Chhabra (2005),
and which allows individual investors to optimally allocate to
categories of risks they face across all life stages and wealth
segments so as to achieve personally meaningful financial
goals.

Through a number of realistic case study examples, we
document the benefits of the approach, which respects the
individual investor’s essential goals with the highest degree
of probability, while allowing for substantial upside potential
that leads to a reasonably high probability of achieving am-
bitious aspirational goals.

In designing and analyzing optimal portfolio
construction methodologies, the research also introduces ro-
bust heuristics, which can be thought of as reasonable ap-
proximations that are not optimal but that can accommodate a
variety of implementation constraints, including the presence
of taxes, the presence of short-sale constraints, the presence
of parameter estimation risk, as well as limited customization
constraints.*

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27 The reason an investor may decide not to secure otherwise affordable important goals is to generate more upside potential and, as a result, increase the probability of achieving aspirational goals.

28 A formal mathematical definition as well as operational verification criteria can be given for the concept of affordability. In the presence of income cash-flows, verification procedures are more complex because of the comparison between current vs. future income in securing goals. The key insight is that future income should be secured at the initial wealth level when securing a goal. Intuitively, this is because this principle allows
investors to use the maximum possible amount of current wealth to generate performance through efficient and well-rewarded investments in rewarded risk factors.

29 Note that investors often hold assets such as cash reserves or residence ownerships that serve the purpose of hedging implicit safety goals.
Yale SOM — EDHEC-Risk Institute Certificate in Risk and Investment Management

This ambitious high-level programme in risk and investment management consists of four seminars that are intended to reflect the major steps in a modern investment process.

Harvesting Risk Premia in Equity and Bond Markets Seminar
May 9-11, 2016 (London); May 18-20, 2016 (New Haven); and Q2 2017

Harvesting Risk Premia in Alternative Asset Classes and Investment Strategies Seminar
June 27-29, 2016 (London); July 11-13, 2016 (New Haven); and Q3 2017

Multi-Asset Multi-Manager Products and Solutions Seminar
December 5-6, 2016 (New Haven); December 12-13, 2016 (London); and Q4 2017

Asset Allocation and Investment Solutions Seminar
Q1 2017

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Since November 23, 2009, EDHEC-Risk Institute has been designing equity smart beta indices.

With live annualised outperformance of 2.41%¹ for more than six years, these Smart Beta 1.0 indices based on the Efficient Maximum Sharpe Ratio methodology have shown that a good diversification method can lead to significant and robust outperformance over cap-weighted indices.

Since 2012, with the Smart Beta 2.0 framework, EDHEC-Risk Institute has created Scientific Beta Smart Factor Indices that are even better diversified and therefore more successful.

The Scientific Beta Smart Factor Indices for the rewarded long-term risk premia of Mid-Cap, Value, Momentum and Low Volatility have all produced positive annualised performance for all regions since they went live on December 21, 2012, with average annualised outperformance over the cap-weighted benchmark of 2.90%.²

The Scientific Beta multi-smart-factor indices, which allocate to these four Smart Factor Indices, have a live track record that is even better than that of our Smart Beta 1.0 offering, with an annualised outperformance of 4.00% compared to their cap-weighted benchmark.³

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 at melanie.ruiz@scientificbeta.com

¹ - The average annualised outperformance of the FTSE EDHEC-Risk Efficient Index series (all regions) is 2.41% compared to its cap-weighted benchmark, computed using daily total returns from November 23, 2009 (live date) to December 31, 2015. The benchmark used is a cap-weighted portfolio of all stocks in the respective Scientific Beta universes.
² - Analysis is based on daily total returns from December 21, 2012 to December 31, 2015 for the USA, Eurozone, UK, Developed Europe ex UK, Japan, Developed Asia Pacific ex Japan, Developed ex UK, Developed ex US and Developed regions. The live date of the four Smart Factor Indices – Mid-Cap, Value, Momentum and Low Volatility – is December 21, 2012 for all regions. The benchmark used is a cap-weighted portfolio of all stocks in the respective Scientific Beta universes. The average outperformance for each factor across all regions is as follows: Mid-Cap (2.62%), Value (1.15%), Momentum (4.31%) and Low Volatility (3.50%), leading to an average across all four factors of 2.90%. All statistics are annualised. Source: scientificbeta.com.
³ - The average live outperformance across all Scientific Beta developed regions of Scientific Beta Multi-Beta Multi-Strategy (Equal Weight and Relative Equal Risk Contribution) indices is 4.00% and 3.77% respectively, while that of the Efficient Maximum Sharpe Ratio strategy in the same period is 2.85%. This live analysis is based on daily total returns in the period from December 20, 2013 (live date) to December 31, 2015, for the following developed world regions – USA, Eurozone, UK, 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. Information containing any historical information, data or analysis should not be taken as an indication or guarantee of any future performance, analysis, forecast or prediction. Past performance does not guarantee future results.