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SPECIAL ISSUE: SMART FACTOR INDEXING

Research for Institutional Money Management

EDHEC-RISK Institute

LIVE IS BETTER

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

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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 regions in question are the USA, UK, Eurobloc, Japan, Developed Asia-Pacific ex Japan and Developed World. 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.

INTRODUCTION

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

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.

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www.edhec-risk.com
CONTRIBUTORS | research@edhec-risk.com

Noël Amenc
Professor of Finance

Felix Goltz
Head of Applied Research

Lionel Martellini
Director, EDHEC-Risk Institute

Vincent Milhau
Head of Research

Sivagaminathan Sivasubramanian
Quantitative Analyst

Jakub Ulahel
Quantitative Research Analyst

INDEXES

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

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

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

Sivagaminathan Sivasubramanian
Quantitative Analyst,
ERI Scientific Beta

INTRODUCTION

Unlike asset managers, index providers are not subject to AIMR-PPS (Association for Investment Management and Research Performance Presentation Standards) or GIPS (Global Investment Performance Standards)-type rules when presenting the performance of their indexes. In the past several years, with the development of smart beta offerings, which make the same promises as asset managers, we have been seeing performance presentations that have been 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.

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 returns relative to a cap-weighted (CW) benchmark of the Norwegian Oil Fund's actively managed portfolio can be explained by exposure to a set of well-documented alternative risk factors. The authors concluded that after taking into account such exposures, active management did not have any meaningful impact on the risk and return of the portfolio. This discussion of active managers' sources of outperformance has naturally led to factor indexes being considered as a more cost-efficient, straightforward and transparent way of implementing such factor tilts. Such indexes are typically marketed on the basis of back-tested performance over relatively short time periods (10 to 15 years). This article looks at a more meaningful performance assessment for a set of factor indexes. We look at both long-term performance over a period of 40 years, which also allows us to assess the consistency of performance within sub-periods, and live performance, which is free from concerns about relying on back-tested data for performance assessment. This double assessment of long-term and live performance should provide more meaningful insights than an analysis of back-tested performance over a short period. Indeed, stellar back-test performance is of little interest if it is not consistent with the range of outcomes observed within sub-periods over a long-term assessment, or if the actual live performance of the indexes is not good.

In this article we discuss four risk factors that are well documented in the academic literature and popular among practitioners and index providers — Value, Momentum, Low Volatility and Value. While index providers often employ additional factors in more recent offerings, such as quality-related factors, we focus here on the four main factors for which there is a substantial post-publication period regarding the academic evidence, and for which live performance of indexes tilting to the factor is available over a meaningful time period. Fama and French have identified that value (book-to-market) and size (market cap) explain average asset returns as a complement to the market beta (Fama and French, 1993). Carhart (1997) empirically proved the existence of another priced factor — the momentum factor. The low volatility factor, which qualifies as an anomaly rather than a risk factor, is the result of the famous "volatility puzzle," which states that low-volatility stocks tend to outperform high-volatility stocks in the long run (Ang et al., 2006). The existence of premia for these factors has not only been documented empirically, but is also explained by a sound economic rationale. As shown in Exhibit 2, such premia can be understood either as compensation for taking on different types of risk, or as exploiting systematic errors by investors which lead to mispricing that persists because of limits to arbitrage.

EXHIBIT 1

Factor indexes from various providers.

Factor Exposure	Index Provider	Index Name
VALUE	MSCI	MSCI Enhanced Value Index MSCI Value Weighted Index
	Russell	Russell 1000 Value Index Russell 1000 Pure Value Index Russell 1000 HE Value Index
	S&P	S&P 500 Enhanced Value Index S&P Intrinsic Value Weighted Index S&P 500 Pure Value Index S&P 500 Value Index
	FTSE	FTSE Value Index FTSE RAFI Index
SIZE	MSCI	MSCI USA Equal Weight Index MSCI USA Size Tilt Index
	Russell	Russell MidCap Index Russell Equal Weighted Index
	S&P	S&P 500 Equal Weight Index S&P Mid Cap Index
MOMENTUM	FTSE	FTSE Global Factor Momentum Index FTSE Global Factor Residual Momentum Index
	MSCI	MSCI Momentum Index MSCI Momentum Tilt Index
	Russell	Russell High Efficiency Momentum Index Russell Axioma High Momentum Index
LOW VOLATILITY	MSCI	MSCI Volatility Tilt Index MSCI Risk Weighted Index MSCI Minimum Volatility Index
	Russell	Russell High Efficiency Low Volatility Index Russell Axioma Low Volatility Index

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 volatility and tracking error, resulting in at best marginal gains in risk-adjusted performance, before taking into account the costs of severely heightened turnover and reduced liquidity associated with narrower selections. 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. It is evident 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. 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 factor exposures in an efficient and well-diversified way. The main idea is to apply a smart weighting scheme to an explicit selection of stocks 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[1], 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 Deconcentration, 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 live track record performance of the four smart factor indexes that harvest 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

EXHIBIT 2

Economic Rationale of Factors

	Risk-Based Explanation	Behavioral Explanation
VALUE	Costly reversibility of assets in place: high sensitivity to economic shocks in bad times	Overreaction to bad news and extrapolation of the recent past leads to under-pricing
SIZE	High-expected-growth firms are more sensitive to shocks to expected growth	Investor overconfidence and self-attribution bias leads to returns continuation in the short term
MOMENTUM	Liquidity-constrained investors have to sell leveraged positions in low-risk assets in bad times when liquidity constraints become binding	Disagreement of investors about high-risk stocks leads to overpricing due to short-sale constraints
LOW RISK	Low liquidity, high distress and downside risk is compensated by higher returns	Limited investor attention to smaller cap stocks

EXHIBIT 3

Taken from Amenc et al (2016) - Performance of Cap-Weighted and Equal-Weighted Factor Indexes.
The period of analysis is 31-Dec-1974 to 31-Dec-2014 (40 years). All figures reported are average figures across six factors – size, momentum, low volatility, value, low investment, and high profitability. All factor-tilted portfolios are rebalanced annually on the 3rd Friday in June. The analysis is done using weekly total returns (dividends reinvested) in USD. The portfolios are constructed using a US stock universe that contains the 500 largest stocks by total market cap. The market-cap-weighted index of these 500 stocks is the benchmark. The yield on secondary market US Treasury Bills (3M) is the risk-free rate. All risk and return statistics are annualized and the Sharpe ratio and information ratio are computed using annualized figures. Outperformance probability (3 years) is the probability of obtaining positive relative returns if one invests in the strategy for a period of 3 years at any point during the history of the strategy. It is computed using a rolling window of length 3 years and step size 1 week. Average relative returns in positive (negative) periods is the mean of only positive (negative) rolling 3-year annualized relative returns. Extreme relative returns in positive (negative) periods are the 95th (5th) percentile of only positive (negative) rolling 3-year annualized relative returns. Data sources: CRSP and WRDS.

		Broad Cap Weighted	Top 50% Stocks Selected by Factor Score		Top 20% Stocks Selected by Factor Score	
			Cap Weighted	Equal Weighted	Cap Weighted	Equal Weighted
Ann. Returns		12.26%	13.87%	16.01%	14.99%	16.62%
Ann. Volatility		16.09%	16.04%	16.64%	17.12%	17.37%
Sharpe Ratio		0.44	0.55	0.66	0.58	0.67
Ann. Rel. Returns		-	1.61%	3.75%	2.73%	4.36%
Ann. Tracking Error		-	4.61%	5.74%	7.53%	7.79%
Information Ratio		-	0.33	0.66	0.36	0.56
Outperf. Probability (3Y)		-	68.12%	76.04%	70.06%	72.94%
Positive Periods	Avg. Rel. Ret.	-	3.22%	5.60%	5.33%	7.05%
	Extreme Rel. Ret.	-	7.96%	13.63%	12.47%	16.32%
Negative Periods	Avg. Rel. Ret.	-	-2.35%	-3.92%	-3.56%	-3.89%
	Extreme Rel. Ret.	-	-6.71%	-9.94%	-9.24%	-9.48%

EXHIBIT 4

Taken from Amenc et al (2016) - Implementation of Cap-Weighted and Equal-Weighted Factor Indexes.
All figures reported are average figures across six factors – size, momentum, low volatility, value, low investment, and high profitability. All factor-tilted portfolios are rebalanced annually on the 3rd Friday in June. The analysis is done using weekly total returns (dividends reinvested) in USD. The portfolios are constructed using a US stock universe that contains the 500 largest stocks by total market cap. The market-cap-weighted index of these 500 stocks is the benchmark. The reported turnover is Annual 1-Way Turnover and is averaged over 40 annual rebalancings in the period 31-Dec-1974 to 31-Dec-2014. Days-to-Trade or DTT of a stock is the number of days required to trade total stock position in the portfolio of $1 billion, assuming that 10% of 'Average Daily Traded Volume (ADTV)' can be traded every day. For each portfolio, the reported DTT value is the 95th percentile of DTT values across all 10 yearly rebalancings in the period 31-Dec-2004 to 31-Dec-2014 and across all stocks. Data sources: CRSP and WRDS.

	Broad Cap Weighted	Top 50% Stocks Selected by Factor Score		Top 20% Stocks Selected by Factor Score	
		Cap Weighted	Equal Weighted	Cap Weighted	Equal Weighted
Ann. 1-Way Turnover	2.68%	29.25%	32.58%	48.15%	48.64%
Days-to-Trade	0.20	0.82	1.56	1.41	2.35

[1] *Amenc, Noël , Felix Goltz, Ashish Lodh, and Lionel Martellini 2014, "Towards Smart Equity Factor Indices: Harvesting Risk Premia without Taking Unrewarded Risks", Journal of Portfolio Management*

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[2], 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 3.87% 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 can not 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 probability of outperformance 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.

EXHIBIT 5

USA Long-Term Track Record (LTTR) Performance (40 Years).
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.

USA LTTR 31-Dec-1974 to 31-Dec-2014	Broad Cap Weighted	Scientific Beta USA LTTR Diversified Multi-Strategy Indexes				Average of the 4 Smart Factor Indexes
		Mid Cap	High Momentum	Low Volatility	Value	
Annual Returns	12.16%	16.75%	15.65%	15.03%	16.70%	16.03%
Volatility	17.12%	16.57%	16.12%	14.16%	16.37%	15.81%
Sharpe Ratio	0.41	0.70	0.65	0.70	0.71	0.69
Relative Returns	-	4.59%	3.49%	2.87%	4.54%	3.87%
Tracking Error	-	6.38%	4.72%	6.04%	5.56%	5.68%
Information Ratio	-	0.72	0.74	0.48	0.82	0.69

EXHIBIT 6

Probability of Outperformance.
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 three-month U.S. Treasury Bill and the benchmark is the cap-weighted reference of the 500 largest stocks in the United States. Outperformance Probability (one, three and five years) is the historical empirical probability of outperforming the benchmark over typical investment horizons of one, three and five years irrespective of the entry point in time. It is computed using a rolling-window analysis of one-, three- and five-year window length and one-week step size. The last column indicates the probability of all four smart factor indexes outperforming simultaneously over one-, three- and five-year horizons.

USA LTTR 31-Dec-1974 to 31-Dec-2014	Broad Cap Weighted	Scientific Beta USA LTTR Diversified Multi-Strategy Indexes				Average of the 4 Smart Factor Indexes	Four indexes outperforming simultaneously
		Mid Cap	High Momentum	Low Volatility	Value		
Probability of Outperformance (1Y)	-	67.78%	67.24%	66.06%	70.83%	67.98%	48.18%
Probability of Outperformance (3Y)	-	74.38%	83.13%	76.04%	78.73%	78.07%	66.51%
Probability of Outperformance (5Y)	-	78.94%	91.25%	85.39%	88.40%	86.00%	75.77%

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 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 (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 very well in bear markets (information ratio of 1.04), but poorly in bull 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 0.41). 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 over-weighted 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 too.

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 Scientific Beta 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[3]. 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

EXHIBIT 7

USA Long Term Track Records (LTTR) (40 Year) — Conditional Performance.
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 3-month U.S. Treasury Bill and the benchmark is the cap-weighted reference of the 500 largest stocks in the United States.

PANEL A – Bull/Bear Market Conditions

The exhibit shows relative performance of Multi-Strategy Factor Indexes for four factor tilts — mid cap, high momentum, low volatility and value, in two distinct markets — bull markets and bear markets. Calendar quarters with positive market index returns comprise bull markets and the rest constitute bear markets. All statistics are annualized.

USA LTTR 31-Dec-1974 to 31-Dec-2014	Scientific Beta USA LTTR Diversified Multi-Strategy Indexes				Average of the 4 Smart Factor Indexes
	Mid Cap	High Momentum	Low Volatility	Value	
BULL MARKETS					
Relative Returns	5.26%	3.03%	-0.85%	3.76%	2.80%
Tracking Error	5.59%	3.96%	5.03%	4.85%	4.85%
Information Ratio	0.94	0.77	-0.17	0.78	0.58
BEAR MARKETS					
Relative Returns	3.27%	3.90%	8.35%	5.36%	5.22%
Tracking Error	8.02%	6.22%	8.01%	7.01%	7.31%
Information Ratio	0.41	0.63	1.04	0.77	0.71

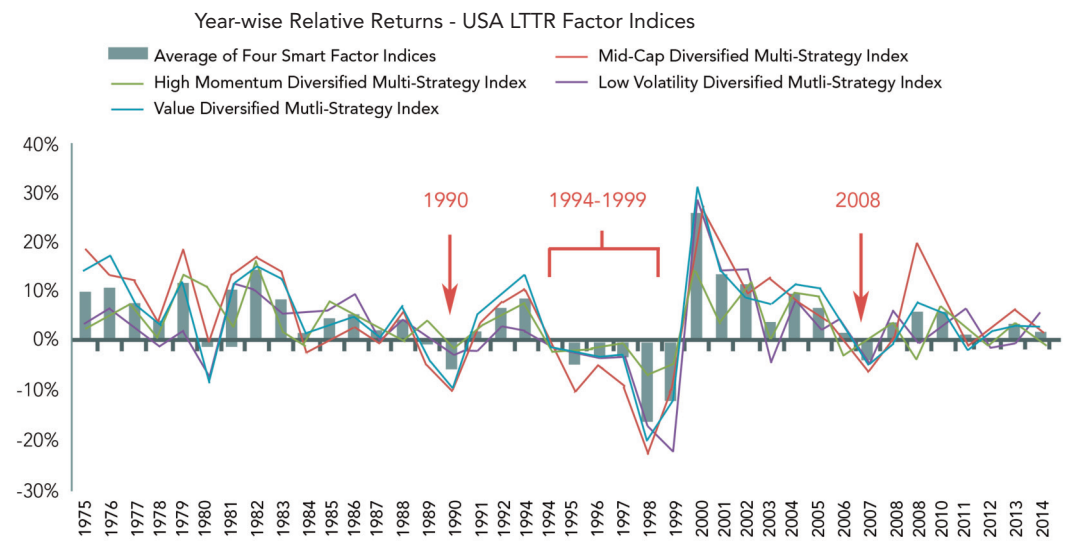
PANEL B – Extreme Bull/Bear Market Conditions

The exhibit shows relative performance of Multi-Strategy Factor Indexes for four factor tilts — mid cap, high momentum, low volatility and value, in extreme market conditions. The top 25% of quarters with highest market returns are considered extremely bullish and the bottom 25% quarters with the lowest returns are considered extremely bearish.

USA LTTR 31-Dec-1974 to 31-Dec-2014	Scientific Beta USA LTTR Diversified Multi-Strategy Indexes				Average of the 4 Smart Factor Indexes
	Mid Cap	High Momentum	Low Volatility	Value	
EXTREME BULL MARKETS					
Relative Returns	10.40%	3.49%	-5.90%	3.51%	2.88%
Tracking Error	6.13%	4.51%	5.19%	5.25%	5.27%
Information Ratio	1.70	0.77	-1.14	0.67	0.50
EXTREME BEAR MARKETS					
Relative Returns	2.66%	3.81%	8.50%	4.95%	4.98%
Tracking Error	8.43%	6.52%	8.45%	7.37%	7.69%
Information Ratio	0.31	0.58	1.01	0.67	0.64

EXHIBIT 8

USA Long Term Track Record (40 Year) — Year-wise Performance.
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.



[3] As per the MSCI World Value Index factsheet, the MSCI World Value Index underperforms the MSCI World Index by 1.7% over the past three-year period as of Dec. 31, 2015. As per the FTSE Developed Factor Indices factsheet, the FTSE Developed World Value Index underperforms the FTSE Developed World Index by 1.3% over the past three-year period as of Dec. 31, 2015.

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 2.01), 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 focus on the performance observed after the commercial launch of the index.

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. •

EXHIBIT 9

Live Track Record Performance — Developed World — Conditional Performance Analysis.
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.

Developed World 21-Dec-2012 to 31-Dec-2015	MSCI World	Scientific Beta Developed World Diversified Multi-Strategy Indexes				Average of the 4 Smart Factor Indexes
		Mid Cap	High Momentum	Low Volatility	Value	
Annual Returns	10.06%	11.93%	12.80%	12.56%	10.18%	11.87%
Volatility	10.86%	10.04%	10.37%	8.96%	10.42%	9.95%
Sharpe Ratio	0.92	1.18	1.23	1.40	0.97	1.20
Relative Returns	-	1.87%	2.74%	2.50%	0.13%	1.81%
Tracking Error	-	2.48%	2.51%	3.15%	1.96%	2.52%
Information Ratio	-	0.75	1.09	0.79	0.06	0.68

EXHIBIT 10

USA Long Term Track Records (LTTR) (40 Year) — Conditional Performance.
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.

PANEL A – Bull/Bear Market Conditions

The exhibit shows relative performance of Multi-Strategy Factor Indexes for four factor tilts — mid cap, high momentum, low volatility and value, in two distinct markets — bull markets and bear markets. Calendar quarters with positive market index returns comprise bull markets and the rest constitute bear markets. All statistics are annualized.

Developed World 21-Dec-2012 to 31-Dec-2015	Scientific Beta USA LTTR Diversified Multi-Strategy Indexes				Average of the 4 Smart Factor Indexes
	Mid Cap	High Momentum	Low Volatility	Value	
BULL MARKETS					
Relative Returns	2.02%	2.13%	1.33%	0.70%	1.55%
Tracking Error	2.47%	2.55%	3.07%	1.88%	2.49%
Information Ratio	0.82	0.83	0.43	0.37	0.61
BEAR MARKETS					
Relative Returns	1.47%	4.95%	7.09%	-1.73%	2.94%
Tracking Error	2.56%	2.31%	3.53%	2.34%	2.68%
Information Ratio	0.58	2.14	2.01	-0.74	1.00

PANEL B – Extreme Bull/Bear Market Conditions

The exhibit shows relative performance of Multi-Strategy Factor Indexes for four factor tilts — mid cap, high momentum, low volatility and value, in extreme market conditions. The top 25% of quarters with the highest market returns are considered extremely bullish and the bottom 25% of quarters with the lowest returns are considered extremely bearish.

Developed World 21-Dec-2012 to 31-Dec-2015	Scientific Beta USA LTTR Diversified Multi-Strategy Indexes				Average of the 4 Smart Factor Indexes
	Mid Cap	High Momentum	Low Volatility	Value	
EXTREME BULL MARKETS					
Relative Returns	1.15%	4.65%	-2.22%	0.21%	0.95%
Tracking Error	2.26%	2.06%	2.65%	1.62%	2.15%
Information Ratio	0.51	2.26	-0.84	0.13	0.52
EXTREME BEAR MARKETS					
Relative Returns	0.67%	3.07%	3.99%	-1.49%	1.56%
Tracking Error	2.52%	2.30%	3.21%	2.18%	2.55%
Information Ratio	0.27	1.34	1.24	-0.68	0.54

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EXHIBIT 11

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.

USA LTTR 31-Dec-1974 to 31-Dec-2014	Broad Cap-Weighted	Mid Cap		High Momentum		Low Volatility		Value		Average of 4 smart factor indexes	
		Cap-Weighted	Diversified Multi-Strategy	Cap-Weighted	Diversified Multi-Strategy	Cap-Weighted	Diversified Multi-Strategy	Cap-Weighted	Diversified Multi-Strategy	Cap-Weighted	Diversified Multi-Strategy
Ann. Returns	12.16%	15.49%	16.75%	13.10%	15.65%	12.40%	15.03%	13.66%	16.70%	13.66%	16.03%
Ann. Volatility	17.12%	17.59%	16.57%	17.30%	16.12%	15.50%	14.16%	17.83%	16.37%	17.06%	15.81%
Sharpe Ratio	0.41	0.59	0.70	0.46	0.65	0.47	0.70	0.48	0.71	0.50	0.69
Ann. Excess Returns	-	3.33%	4.59%	0.94%	3.49%	0.24%	2.87%	1.51%	4.54%	1.51%	3.87%
Ann. Tracking Error	-	5.75%	6.38%	3.50%	4.72%	4.47%	6.04%	4.53%	5.56%	4.56%	5.68%
Information Ratio	-	0.58	0.72	0.27	0.74	0.05	0.48	0.33	0.82	0.31	0.69

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.

Developed World 21-Dec-2012 to 31-Dec-2015	MSCI World	Mid Cap		High Momentum		Low Volatility		Value		Average of 4 smart factor indexes	
		Cap-Weighted	Diversified Multi-Strategy	Cap-Weighted	Diversified Multi-Strategy	Cap-Weighted	Diversified Multi-Strategy	Cap-Weighted	Diversified Multi-Strategy	Cap-Weighted	Diversified Multi-Strategy
Ann. Returns	10.06%	11.45%	11.93%	11.57%	12.80%	10.23%	12.56%	7.84%	10.18%	10.27%	11.87%
Ann. Volatility	10.86%	10.82%	10.04%	11.04%	10.37%	9.76%	8.96%	11.40%	10.42%	10.75%	9.95%
Sharpe Ratio	0.92	1.05	1.18	1.04	1.23	1.04	1.40	0.68	0.97	0.96	1.20
Ann. Excess Returns	-	1.40%	1.87%	1.51%	2.74%	0.17%	2.50%	-2.22%	0.13%	0.22%	1.81%
Ann. Tracking Error	-	2.40%	2.48%	2.01%	2.51%	2.18%	3.15%	1.87%	1.96%	2.12%	2.52%
Information Ratio	-	0.58	0.75	0.75	1.09	0.08	0.79	-1.19	0.06	0.06	0.68

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

INDEXES

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

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

Sivagaminathan Sivasubramanian
Quantitative Analyst,
ERI Scientific Beta

Jakub Ulahel
Quantitative Research Analyst,
ERI Scientific Beta

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 consensual 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

Brief Methodology Description of Various Value Factor Indexes.
Source: Methodology description documents from the respective index providers.

Index Name	Factor Definition	Stock Selection	Weighting Scheme
Scientific Beta Value Multi-Strategy Index	Book-to-Market	50% of stocks in the universe based on factor score	Diversified Multi-Strategy[4]
FTSE RAFI Developed	Composite of Sales, Cash Flow, Book Value and Dividends	Top 1,000 stocks ranked on composite score	Score Weighting
FTSE Developed Value Factor	Composite of Cash Flow Yield, Earnings Yield and Sales-to-Price	None	Composite score times Market Capitalization
MSCI World Enhanced Value	Composite of Forward Price-to-Earnings, Price-to-Book and Enterprise Value-to-Operating Cash Flow	Fixed number of securities based on flow algorithm with a target 30% cap coverage	Composite score times Market Capitalization
MSCI World Value Weighted	Composite of Book Value, Sales Value, Earnings Value and Cash Earnings Values	None	Ratio of Composite Score and Market Cap
Russell Developed Value	Composite of Book-to-Price, 2-year IBES forecast and 5 year sales per share growth is used to determine either value or growth probability	Stocks with pure value probability (100%) plus a percentage of the middle sector comprised of companies with both value and growth probabilities	Cap-Weighting
Russell Developed LC HE Value	Composite of Book-to-Price and Earnings-to-Price	None	Proprietary algorithm known as 'NLP'
S&P Enhanced Value Developed LMC	Composite of Book Value-to-Price, Earnings-to-Price and Sales-to-Price	Generally 20% of the parent index constituents	Composite score times Market Capitalization
S&P Intrinsic Value Weighted Developed	Book Value and Discounted Adjusted Earnings	None	Score Weighting
S&P Developed BMI Value	Composite of Book Value-to-Price, Cash Flow to Price, Dividend Yield and Sales-to-Price + three growth measures	33% of market cap with the highest value score + some percentage of the blended basket of growth and value	Cap-Weighting

[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 (2015) and Amenc et al. (2014).*

whether a stock is low value or not. Novy-Marx (2015) shows 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 value 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 to the stock selection is either market-cap-weighting or score-based weighting, resulting in a 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 macroeconomic 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.

EXHIBIT 2

Absolute and Relative Performance.
The tables show the performance and risks of the Scientific Beta Value Smart Factor Index and its competitors in the Developed Universe. The analysis is based on daily total return data from Aug. 1, 2005, to Dec. 31, 2014. The time period is chosen based on the longest available historical dataset for all the indexes compared as of Dec. 31, 2014. Return analysis is based on daily data. The MSCI World Index is used as the cap-weighted reference. Yield on Secondary U.S. Treasury Bills (3M) is used as a proxy for the risk-free rate. Data for external indexes come from Bloomberg and DataStream or provider´s official websites. Data for Scientific Beta indexes come from www.scientificbeta.com.

PANEL A – Absolute Performance

Absolute Performance	SciBeta Developed Value Multi-Strategy	FTSE RAFI Developed	FTSE Developed Value Factor	MSCI World Enhanced Value	MSCI World Value Weighted	Russell Developed Value	Russell Developed LC HE Value	S&P Enhanced Value Developed LMC	S&P Intrinsic Value Weighted Developed	S&P Developed BMI Value	MSCI World
Ann. Returns	7.79%	7.00%	6.21%	7.57%	6.02%	5.94%	7.44%	5.64%	6.83%	6.65%	6.63%
Ann. Volatility	17.61%	19.63%	19.16%	20.07%	19.03%	18.67%	19.03%	22.24%	18.12%	18.33%	17.92%
Sharpe Ratio	0.37	0.29	0.25	0.31	0.25	0.25	0.32	0.19	0.30	0.29	0.29
Sortino ratio	0.50	0.40	0.35	0.43	0.34	0.34	0.44	0.27	0.42	0.40	0.41
Cornish-Fisher VaR	1.71%	1.84%	1.81%	1.92%	1.80%	1.77%	1.82%	2.09%	1.73%	1.76%	1.68%
Max DD	57.32%	61.00%	60.47%	61.67%	61.55%	61.02%	61.61%	68.99%	59.08%	61.16%	57.46%

PANEL B – Relative Performance

Relative Performance	SciBeta Developed Value Multi-Strategy	FTSE RAFI Developed	FTSE Developed Value Factor	MSCI World Enhanced Value	MSCI World Value Weighted	Russell Developed Value	Russell Developed LC HE Value	S&P Enhanced Value Developed LMC	S&P Intrinsic Value Weighted Developed	S&P Developed BMI Value
Ann. Excess Returns	1.16%	0.37%	-0.42%	0.95%	-0.61%	-0.69%	0.81%	-0.99%	0.20%	0.02%
Tracking Error	2.42%	4.02%	3.55%	5.26%	2.72%	2.25%	3.90%	9.72%	2.13%	1.87%
Information Ratio	0.48	0.09	-0.12	0.18	-0.22	-0.31	0.21	-0.10	0.09	0.01
Outperformance probability 1Y	70%	55%	43%	51%	45%	40%	55%	49%	56%	52%
Outperformance probability 3Y	74%	60%	11%	53%	10%	13%	49%	19%	49%	50%
Outperformance probability 5Y	100%	61%	18%	38%	13%	7%	81%	26%	78%	40%
5% of Rolling 1-Y Rel. Returns	-3.58%	-4.98%	-4.43%	-8.15%	-4.53%	-4.88%	-4.66%	-12.67%	-2.41%	-3.39%
95% of Rolling 1-Y Tracking Error	4.19%	9.16%	7.80%	9.72%	5.95%	4.32%	8.91%	22.31%	4.56%	3.83%
Cornish-Fisher Relative VaR	0.24%	0.31%	0.29%	0.53%	0.23%	0.20%	0.32%	0.87%	0.19%	0.17%
Max Relative DD	5.68%	13.50%	12.04%	18.09%	11.51%	11.60%	12.24%	28.98%	7.53%	10.20%

Interestingly, while most indexes rely on proprietary value definitions, the only index which follows a straightforward and consensual definition of the value factor as 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 compared 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 and leads to markedly different results.

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 consensual 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[5].

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 deviating 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 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. •

EXHIBIT 3

Factor Exposure of Value-Tilted Indexes in the Developed Universe.
The MSCI World Index is used as the cap-weighted reference. The Market factor is the weekly total return of a cap-weighted index portfolio in excess of the risk-free rate. The Small size factor is long the EW portfolio of market cap deciles 6 to 8 (NYSE, Nasdaq, AMEX) and short the EW portfolio of the largest 30% of stocks. The Value factor is long the EW portfolio of the highest 30% and short the EW portfolio of the lowest 30% of B/M ratio stocks. The Momentum factor is long the EW portfolio of the highest 30% and short the EW portfolio of the lowest 30% of 52-week (minus most recent 4 weeks) past return stocks. The Low Volatility factor is long the EW portfolio of the lowest 30% and short the EW portfolio of the highest 30% of stocks based on past two-year volatility. Yield on Secondary U.S. Treasury Bills (3M) is used as a proxy for the risk-free rate. The analysis is based on weekly total return data from Aug. 1, 2005, to Dec. 31, 2014. The time period is chosen based on the longest available historical dataset common to all the indexes compared as of Dec. 31, 2014. The regression coefficients (betas and alphas) statistically significant at the 95% level are highlighted in bold.

Factor Exposure - SciBeta EW	SciBeta Developed Value Multi-Strategy	FTSE RAFI Developed	FTSE Developed Value Factor	MSCI World Enhanced Value	MSCI World Value Weighted	Russell Developed Value	Russell Developed LC HE Value	S&P Enhanced Value Developed LMC	S&P Intrinsic Value Weighted Developed	S&P Developed BMI Value
Unexplained return	0.66%	-0.22%	-0.81%	**0.41%**	**-0.96%**	-1.42%	0.43%	-1.38%	0.10%	-0.57%
MKT-Rf	**0.98**	**0.98**	**1.01**	**1.02**	**1.00**	**1.01**	**0.97**	**0.99**	**0.99**	**1.00**
SMB	**0.11**	**-0.03**	**-0.05**	**-0.14**	**-0.06**	**0.07**	**0.05**	**-0.14**	**0.03**	**0.13**
HML	**0.16**	**0.35**	**0.22**	**0.31**	**0.25**	**0.29**	**0.29**	**0.58**	**0.08**	**0.20**
MOM	**0.07**	0.00	0.02	**0.05**	**-0.03**	**0.03**	**-0.05**	**-0.07**	0.00	**0.03**
LVOL	0.02	-0.03	**-0.03**	**-0.10**	**-0.03**	**0.04**	**-0.06**	**-0.16**	**-0.04**	**0.02**
R-squared	98.80%	98.00%	98.93%	97.66%	99.57%	99.55%	98.80%	95.17%	99.44%	99.57%
Ann. Standard deviation of residuals	2.09%	2.96%	2.14%	3.38%	1.35%	1.34%	2.29%	5.41%	1.47%	1.31%
Unexplained return/Standard deviation of residuals	0.32	-0.07	-0.38	0.12	-0.71	-1.06	0.19	-0.26	0.07	-0.44

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[5] *Source: the S&P Dow Jones Indices Methodology document entitled "S&P GIVI Indices – Methodology" available at http://us.spindices.com/indices/strategy/sp-intrinsic-value-weighted-global-index-us-dollar*

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%.[1]

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

www.scientificbeta.com

1 - The average annualised relative retum 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.

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Is There Crowding in Smart Beta Strategies?

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

Sivagaminathan Sivasubramanian
Quantitative Analyst,
ERI Scientific Beta

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)[6]), while proponents of traditional cap-weighting say that smart beta is not passive enough (see, for example, Philips et al. (2015[7]).

Among such critiques, a recurring issue is the presumption of a risk of "crowding" in smart beta strategies. For example, Jacobs (2015)[8] 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 overcrowding 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)[9]. 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 premia exist because investors make systematic errors due to behavioral biases such as overreaction or under-reaction to news on a stock, leading to mispricing.

Whether such behavioral biases can persistently affect asset prices is a point of contention, given the presence of smart market participants who do not suffer from these biases. For behavioral explanations to be relevant, it is necessary to assume that — in addition to biases — there are so-called "limits to arbitrage," i.e., some market characteristics, such as short-sale constraints and funding-liquidity constraints, which prevent smart investors from fully exploiting the opportunities arising from the irrational behavior of other investors.

Overall, such economic explanations provide reasons for why factor premia should persist, even if investors are widely aware of them. Some investors will shy away from exploiting the premium even if they are convinced of its existence, simply because they are not willing to take the associated risks, or because they are prevented from going against biased behavior because of institutional constraints.

Disappearing premium or risk premium?

Some who theorize about the existence of crowding argue that the losses occurring in a particular factor at some point in time are evidence of "crowding." For example, Yasancheck and Whitman (2015)[10] argue that "given the increase in popularity of smart beta strategies, there is a similarly increased over-crowding risk, which could result in factor crashes." In the same vein, Jacobs (2015)[11] states that

EXHIBIT 1

Economic Explanations for Selected Factor Premia: Overview.

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

[6] *Yasenchak, Richard, and Philip Whitman, 2015, "Understanding the Risks of Smart Beta, and the Need for Smart Alpha," Intech Janus White Paper, available at <http://ow.ly/WEKQ2>*
[7] *Philips, Christopher, Donald Bennyhoff, Francis Kinniry, Todd Schlanger and Paul Chin, "An evaluation of smart beta and other rules-based active strategies," Vanguard White Paper, available at <http://ow.ly/WELkv>*
[8] *Jacobs, Bruce, 2015, "Invited Editorial: Is Smart Beta State of the Art?" Journal of Portfolio Management, 41 (4), 1-3.*
[9] *Cochrane, John, 1999, "Portfolio Advice for a Multifactor World," Economic Perspectives - Federal Reserve Bank of Chicago, 23(3), 59-78.*
[10] *Yasenchak, Richard, and Philip Whitman, 2015, "Understanding the Risks of Smart Beta, and the Need for Smart Alpha," Intech Janus White Paper, available at <http://ow.ly/WEKQ2>*
[11] *Jacobs, Bruce, 2015, "Invited Editorial: Is Smart Beta State of the Art?" Journal of Portfolio Management, 41(4), 1-3.*

smart beta strategies may be prone to "overvaluation, fragility and even factor crashes as investors withdraw en masse from once-popular but now underperforming factors" and asserts that "we've already seen an example in the collapse of momentum stocks with the tech wreck in 2000."

Given such claims, one can ask whether the losses in a particular factor at a particular point in time are indeed evidence of crowding. Taking the claims above concerning crowding in momentum as an example, is there any empirical evidence that the behavior of momentum was due to overcrowding? Is there any evidence suggesting that these losses in momentum strategies were different from the usual time 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 if the equity market factor has experienced crashes, there must be overcrowding 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 factors 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 (1993)[12] that "we need decades of data for accurate estimates of average expected return. We need such a long period to estimate the average that we have little hope of seeing changes in expected returns." Thus, claiming that factor premia 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 expected that we will observe periods with low returns, and given the uncertainty in estimating returns reliably, any sample-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 (2015a)[13] concluded based on a U.S. sample that the value factor is redundant but Fama and French (2015b)[14] do not find evidence of the redundancy of the value factor in global data and caution that their earlier results on redundancy may be sample-specific. 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 explain the cross-section of expected returns (see Barillas and Shanken (2015)[15]).

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.

EXHIBIT 2

Performance of Value-Tilted Indexes for Global Developed Universe.
All statistics are annualized and daily total returns from 12/31/2005 to 12/31/2015 (10 Years) are used for the analysis. The SciBeta CW Developed - 2000 index is used as the cap-weighted benchmark. The yield on Secondary U.S. Treasury Bills (3M) is used as a proxy for the risk-free rate. The value indexes use a stock selection of 50% of the stocks in the reference universe.

Developed World 31-Dec-2005 to 31-Dec-2015	Broad Cap Weighted	Value	
		Cap-Weighted	Diversified Multi-Strategy
Annual Returns	5.58%	4.32%	6.37%
Volatility	17.34%	19.07%	17.43%
Sharpe Ratio	0.26	0.17	0.30
Annual Relative Returns	-	-1.25%	0.80%
Tracking Error	-	2.87%	2.24%
Information Ratio	-	-0.44	0.36

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 effects in particular smart beta indexes, a small number of recent 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 substantiate their claims about crowding risk, it should be emphasized 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)[16], 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 following 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, return effects are often insignificantly different from zero across the different model specifications, which is hardly strong evidence 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)[17] 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 variables, 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 standard factors. Such non-standard factors are based on variables such as the firm age, corporate governance measures, inventory-related measures, seasonality, revenue surprises, changes in R&D spending, and analyst earnings forecasts[18]. The authors analyze the in-sample result for a return premium over the 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 premia 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 hypothesis that post-publication anomaly returns decay entirely. 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 result is obtained when analyzing a large number of almost 100

[12] *Black, Fischer. "Estimating Expected Return." Financial Analysts Journal, Vol. 49, No. 5 (1993), pp. 36-38.*
[13] *Fama, Eugene, and Kenneth French, 2015a, "A Five-Factor Asset Pricing Model," Journal of Financial Economics, Vol. 116, pp. 1-22.*
[14] *Fama, Eugene, and Kenneth French, 2015b, "International Tests of a Five-Factor Asset Pricing Model," working paper, available at: http://ssrn.com/abstract=2622782*
[15] *Barillas, Francisco, and Jay Shanken, 2015, "Comparing Asset Pricing Models," working paper, available at: http://ssrn.com/abstract=2676709*
[16] *Yost-Bremm, Chris, 2014, "Abnormal Trading Around Common Factor Pricing Models," working paper*
[17] *McLean, R. D. and Pontiff, J., 2015, "Does Academic Research Destroy Stock Return Predictability?" Journal of Finance, forthcoming.*
[18] *These variables are listed in the internet appendix to McLean and Pontiff (2015); see Table I.A.III.*

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 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 disappearing rewards even for an extensive set of factors which may include strategies that do not have a strong risk-based rationale is indeed strong evidence against the theory that 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)[19]). 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-tilted 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."[20] 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 theorists 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. •

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"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 inventive 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 factors.

The mismatch is striking. Many index providers obviously disagree with Fama and French, the godfathers of equity factor research, on how the factors should be defined. In a recent interview[21], Fama commented: "Now everybody talks about value. ... Some stuff is fly-by-night. There are like 45 versions of that and every guy has their own marketing ploy. The acid test is you put it in the three-factor model and it says it is a value portfolio." Indeed, when providers create marketing innovation by tweaking factors, the link with the original academic factor risks being lost. Such a loss implies that a factor index, which is meant to be based on academic groundings for the factor, on thorough empirical evidence and a sound economic rationale, is in fact based only on back-tests of the provider. A crucial question with indexes based on proprietary tweaked factor definitions is therefore to identify potential biases in the back-tested results.

Selection bias

There is a strong risk of data-mining linked to the selection of proprietary factor definitions. Many providers use inventive 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)[22] 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-Marx (2015) argues 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-Marx 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 asselecting, 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.

EXHIBIT 1

Overview of index provider factor definitions.

Provider	Value	Momentum	Quality
Fama-French (1993, 2012, 2015)	Price-to-Book	Past 12-month return (omitting last month)	ROE (operating profits divided by book equity)
Goldman Sachs Equity Factor Index World	Value score from proprietary risk model (Axioma), relative to stock's regional industry group	Residuals from cross-sectional regression of 12-month return (omitting last month) on stock volatility	Composite based on asset turnover, liquidity, ROA, operating CF to assets, accruals, gross margin, leverage
MSCI Multi-Factor Indexes (2013)	Sector-relative composite based on Enterprise Value / Operating CF, Forward P/E, Price-to-Book	Composite score based on excess return divided by ann. volatility over past 12 months and past 6 months	Composite based on return on equity, standard deviation of earnings, debt-to-equity
FTSE Global Factor Index Series	Composite based on Cash Flow-to-Price, Net Income-to-Price, and Country-Relative Sales-to-Price	Mean/Std. dev. of "avg. residual" from 11 rolling window regressions of past 36 months' returns on country and industry index	Composite based on operating CF to debt, net income to assets, annual change in (sales over assets), accruals
Deutsche Bank Equity Factor Indexes	Composite based on inverse of Enterprise Value to EBITDA and dividend yield	Past 12-month return (omitting last month) minus risk adjustment times idiosyncratic volatility score	Composite based on return on invested capital and net operating assets growth

[21] *https://www.dimensional.com/famafrench/videos/dimensionals-david-booth-interviews-eugene-fama.aspx.*
[22] *http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2528780.*
http://docs.edhec-risk.com/mrk/000000/Scientific_Beta_Library/External_use/White_papers/ERI_Scientific_Beta_Publication_Scientfic_Beta_Diversified_Multi-Strategy_Index.pdf"

EXHIBIT 2

Change in factor definitions.

	Scoring 2013	2015	Adjustments 2013	2015
Value	Sales, book value, earnings and cash earnings. Past three-year average values. Simple average across variables.	Price-to-Book Value, Price-to-Forward Earnings and Enterprise Value-to-Cash flow from Operations. Current values. Average of z-score for each variable.	No sector control.	Sector-relative scoring.
Quality	Return on Equity, Debt-to-Equity and Earnings Variability. Average of z-score for each variable.	Return on Equity, Debt-to-Equity and Earnings Variability. Average of z-score for each variable.	No sector control.	Sector-relative scoring.
Size	None: equal-weighting of large/mid cap stocks is prescribed as a way to capture the size premium.	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.	No country or sector control.	Country control (the Proprietary model's descriptor is on a country-relative basis).
Momentum	12-month and six-month local price performance. Simple average of z-scores.	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.	Momentum score is risk-adjusted.	No explicit risk adjustment (use of Proprietary Model exposure).

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-tilted 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 [23]. In fact, index providers[24] have argued that having a consistent set of cap-weighted indexes applying the same rules across regions and leaving no gaps is important in order to avoid unintended exposures and inconsistent investment outcomes. While striving for consistency when creating cap-weighted indexes is commendable, consistency should not be forgotten by the same providers when designing factor indexes.

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[25]. 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 disappointing 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 3

Comparison of old and new indexes.
The table compares the performance of older and newer single-factor MSCI indexes for different time frames before the launch of the corresponding new index, i.e., MSCI Enhanced Value. The analysis is based on daily total return data and statistics are annualized. Measures based on volatility and tracking error use weekly steps. The MSCI World Index is used as the cap-weighted reference in the Developed Universe. Yield on Secondary U.S. Treasury Bills (3M) is used as a proxy for the risk-free rate. Data for MSCI indexes comes from Bloomberg and DataStream.

Developed Markets	1Y prior to launch of new index (08/11/2013-08/11/2014)		10Y prior to launch of new index (08/11/2004-08/11/2014)	
	MSCI World Value Weighted (old index)	MSCI World Enhanced Value (new index)	MSCI World Value Weighted (old index)	MSCI World Enhanced Value (new index)
Annualized Return	13.92%	17.32%	7.92%	10.20%
Annualized Volatility	9.87%	10.75%	20.05%	21.55%
Sharpe Ratio	1.41	1.61	0.32	0.40
Excess Return	-0.28%	3.11%	-0.22%	2.06%
Tracking Error	1.37%	3.06%	2.70%	4.75%
Information Ratio	-0.21	1.02	-0.08	0.43

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.

Of course, it would be straightforward to enhance back-tested performance using proprietary factors relative to these standard factors, given the ease of access to stock-level characteristics and the ease of running such computations. However, while they necessarily do not constitute the most enhanced back-test performance, factor indexes which draw on standard factor definitions hold the promise to deliver robust performance out-of-sample, or on a live basis. As an illustration, in Exhibit 5 we provide the live performance for the four Scientific Beta Multi-Strategy Factor Indexes which have almost three years of live performance as of today. It is noteworthy that all four factor indexes provide positive relative returns since the live date. This finding of strong live performance of very parsimonious and straightforward factor definitions in itself may perhaps question the need for further enhancing factor definitions, especially if one considers the data-mining risks associated with such enhancements.

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] *https://www.msci.com/documents/10199/2c8ba380-f990-4efe-8532-500307e046ee*
[24] *http://www.napf.co.uk/PolicyandResearch/DocumentLibrary/~/media/Policy/Documents/0371-Indices-and-benchmarks-made-simple.pdf*
[25] *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-elaboration 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.

Factor	Factor Definition	Period	Premium	t-stat	Source
Market	Excess returns of cap-weighted equity index	1926-2008	7.72% (annual)	3.47	Ang et al. (2009)
Low Risk	Stocks with low vs. high risk (beta, volatility or idiosyncratic volatility	1926-2012	0.70% (monthly)	7.12	Frazzini-Pedersen (2014)
Size	Stocks with low vs. high market cap	1926-2008	2.28% (annual)	1.62	Ang et al. (2009)
Value	Stocks with high vs. low book-to-market	1926-2008	6.87% (annual)	3.27	Ang et al. (2009)
Momentum	Stocks with high vs. low returns over past 12 months (omitting last month)	1926-2008	9.34% (annual)	5.71	Ang et al. (2009)
Profitability	Stocks with high vs. low profitability (e.g. return on equity or gross profitability)	1963-2013	0.17% (monthly)	2.79	Fama-French (2014)
Investment	Stocks with low vs. high investment (change in total assets)	1963-2013	0.22% (monthly)	3.72	Fama-French (2014)

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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.

Developed World 12/21/2012 to 09/30/2015	MSCI World	Scientific Beta Diversified Multi-Strategies				Average of the 4 Smart Factor Indexes
		Mid Cap	Momentum	Low Volatility	Value	
Absolute Performance						
Average Annual Returns	8.86%	11.19%	11.82%	11.60%	9.53%	11.03%
Volatility	11.09%	10.23%	10.76%	9.07%	10.71%	10.19%
Sharpe Ratio	0.80	1.09	1.09	1.27	0.89	1.09
Relative Performance						
Annual Relative Returns	-	2.32%	2.96%	2.73%	0.67%	2.17%
Tracking Error	-	2.61%	2.61%	3.62%	1.93%	2.69%
Information Ratio	-	0.89	1.13	0.76	0.35	0.78

INDEXES

A Comprehensive Investment Framework for Goals-Based Wealth Management

Lionel Martellini
Professor of Finance,
EDHEC Business School,
Director, EDHEC-Risk Institute

Vincent Milhau
Head of Research,
EDHEC-Risk Institute

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 expected shortfall in case adverse market conditions make it unfeasible to achieve those goals. The need to design an asset allocation solution that is a function of the kinds of particular risks to which the investor is exposed, or needs to be exposed to fulfill goals, as opposed to purely focusing on the risks impacting the market as a whole, makes the use of Modern Portfolio Theory or standard portfolio optimization techniques mostly inadequate.

While the efficient management of all risk buckets, vs. market risk alone, is a central component of the Wealth Allocation Framework (WAF) introduced in Chhabra (2005), the practical implications of this insight have not been fully exploited to date. Most financial advisors still maintain a sole focus on market risks taken in isolation, with investors' preferences crudely summarized in terms of a simple risk-aversion parameter.

The focus of recent research that we conducted with the support of Merrill Lynch Wealth Management[26] 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 concentrated risk exposures — for example, under the form of equity ownership in a private business.

Introducing a formal goals-based wealth management framework

In a nutshell, the goals-based wealth management framework includes two distinct elements. On the one hand, it involves the disaggregation of investor preferences into groups of goals that have similar key characteristics, with priority ranking and term structure of associated liabilities, and on the other hand it involves the mapping of these groups to optimized performance or hedging portfolios possessing corresponding risk and return characteristics, as well as an efficient allocation to such performance and hedging portfolios. More precisely, 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

[26] Deguest, R., L. Martellini, V. Milhau, A. Suri and H. Wang, March 2015, "Introducing a Comprehensive Investment Framework for Goals-Based Wealth Management," EDHEC Risk Institute Publication produced with the support of Merrill Lynch Wealth Management.

the investor's existing assets and liabilities, as well as an estimate of future consumption and revenue streams, and on the other hand a list of the meaningful goals that should be integrated 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 goals[27]; and 3) aspirational goals (AG), which are non-affordable (and non-secured) goals[28].

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 funding status of the goal (i.e., its affordability or non-affordability) depends on the present 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 (GHP) 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 consumption cash-flows are 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 multiple-horizon 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 strategy[29].

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 financial 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 investing 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 traditional clear-cut split between active vs. passive portfolios (see Amenc et al. (2014)) and offer a set of cost-efficient and attractive 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, and investing 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 achievement of important and aspirational goals, is in fact a specific case of a wider class of (in general) dynamic GBI strategies. These strategies advocate that the allocation to PSPs vs. GHPs should be taken as some function of the current wealth level and the present value of the fraction of essential goals that is not financed by future cash inflows, with the key property that this function (whose parameters in general depend on market conditions) should converge to zero when wealth converges to levels required for securing essential 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 implementation, 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 insurance component only when most needed.

This class of strategies, which are reminiscent of constant proportion portfolio insurance strategies extended to an integrated 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 dialogue with the investors, and provides a set of subjective outputs (probability of reaching goals and associated expected shortfall) as well as objective outputs (allocation recommendations 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 management tool meant to facilitate the relationship with the investor and the associated reporting requirements, and an asset management tool, dedicated to the execution of portfolio recommendations.

For a given allocation strategy (e.g., a fixed-mix rebalancing toward the investor's current allocation or a more complex 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 expected 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 modern 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 understanding of the investor problem. Individual investors do not need investment products with alleged superior performance; 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 framework, which formalizes the goals-based risk allocation approach 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 ambitious aspirational goals.

In addition to developing and analyzing optimal portfolio construction methodologies, the research also introduces robust heuristics, which can be thought of as reasonable approximations for optimal strategies 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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Ellis, C., *2014, The Rise and Fall of Performance Investing, Financial Analysts' Journal, 70, 4, 14-23.*

[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 competition between current wealth vs. future income in securing goals. The key insight is that future income should be favored over initial wealth 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.*

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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 regions in question are the USA, UK, Eurobloc, Japan, Developed Asia-Pacific ex Japan and Developed World. 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.