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Research for Institutional Money Management

EDHEC-RISK Institute

INTRODUCTION

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It is my pleasure to introduce the latest issue of the Research for Institutional Money Management supplement to P&I, which aims to provide asset owners with an academic research perspective on the most relevant issues in the industry today.

For asset owners pursuing a passive equity investment strategy, in addition to the question of selecting a suitable equity index as a stand-alone investment, the question of combining different smart beta strategies naturally arises in the context of an extensive range of smart beta offerings. Our first article addresses the issue of combining several smart beta strategies, clarifies the conceptual underpinnings and relevant questions arising when considering smart beta index combinations and introduces the Scientific Beta six factor multi-smart factor indexes.

"Monkey portfolio" proponents argue that all equity smart beta strategies generate performance that is similar to results obtained by any random portfolio strategy. In our article, we analyze these claims using test portfolios that follow commonly employed methodologies for explicit factor-tilted indexes. Our results show that smart beta strategies display exposure to a variety of factors, and there are pronounced differences in factor exposures across different strategies. An important implication of our results is that a careful assessment of investment philosophy and index design is indeed relevant as such strategies do not behave like monkey portfolios.

We examine conventional wisdom on the performance drivers of equity smart beta performance by drawing on conceptual considerations and empirical evidence. The analysis shows that, more often than not, superficially convincing claims about smart beta performance drivers stand on shaky foundations. Our analysis also shows that considering a breadth of evidence and conceptual considerations may perhaps lead to more balanced conclusions and a more nuanced understanding of smart beta performance.

We look at whether it would make sense for a pension fund to hold a customized equity portfolio engineered to exhibit enhanced liability-hedging properties vs. holding a broad off-the-shelf equity index. We conclude that investors with liability constraints will strongly benefit from switching their equity portfolio from a cap-weighted benchmark to a dedicated liability-friendly portfolio based on the selection of stocks which combine low volatility and high dividend yields and a constrained minimum-variance optimization. Within the S&P 500 universe, liability-driven investment (LDI) strategies switching to such a liability-friendly equity benchmark starting from a 40% allocation to S&P 500 index would benefit from a close to +1.8% per annum excess return over the 1975-2014 period without a corresponding increase in funding ratio volatility.

In research supported by Lyxor Asset Management, we analyze whether systematic rules-based strategies based on investible versions of traditional and alternative factors allow for satisfactory in-sample and out-of-sample replication of hedge fund performance, and more generally whether suitably designed risk allocation strategies provide a cost-efficient way for investors to obtain attractive exposure to alternative factors, regardless of whether or not they can be regarded as proxies for any particular hedge fund strategy. Our results suggest that risk parity strategies applied to alternative risk factors could be a better alternative than hedge fund replication for harvesting alternative risk premia in an efficient way.

We discuss the need for the investment industry to evolve beyond standard product-based, market-centered approaches and to start providing both individuals with meaningful retirement investment solutions. Well-designed retirement solutions would allow individual investors to secure the kind of replacement income in retirement needed to meet their essential consumption goals, while generating a relatively high probability for them to achieve their aspirational consumption goals. There is currently a unique opportunity for the financial industry to add value for society as a whole.

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

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INDEXES

Comprehensive and Well-Diversified Access to Rewarded Equity Factors: a Six-Factor Smart Beta Strategy

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Smart beta product offerings have proliferated over the past decade, offering investors an ample choice of different factors and different weighting schemes to select from for a relevant smart beta index. However, in addition to the question of selecting a suitable index as a stand-alone investment, the question of combining different smart beta strategies naturally arises in the context of an extensive range of smart beta offerings. This article addresses the issue of combining several smart beta strategies, clarifies the conceptual underpinnings and relevant questions arising when considering smart beta index combinations, and introduces the Scientific Beta six factor multi-smart factor indexes.

We first look at the six commonly rewarded risk factors — Size, Value, Momentum, Low Risk, Investment and Profitability — and why they are rewarded. We follow that with a discussion on the design requirements for suitable multi-factor indexes. Considerations include how to ensure efficient and investible exposure to each of the relevant factors, and the rationale for combining the different factors. We then assess the performance of a combination of six well-diversified single-factor indexes that provides comprehensive access to the underlying factor indexes.

How to choose the relevant factors?

With the proliferation of factor indexes in the market, investors face an important decision on which factors to include in their portfolios. In this section, we address this question in detail. The following six factors are widely documented in the academic literature — Size, Value, Momentum, Low Risk, Investment and Profitability. The first important characteristic to assess a factor is the presence of empirical evidence of factor premia over sufficiently long-term data in the literature. In fact, studies on U.S. equity data typically span at least 40 years of data, and in many cases, data goes as far back as the 1920s. For the purpose of illustration, the table below provides an overview of results obtained on the key factors with long-term U.S. data.

The second empirical assessment is to check if the factors are robust across different regions and asset classes. Research has made considerable progress in this direction over the past decade, with surprisingly strong confirmation of the U.S. equity results in other investment universes. Exhibit 2 presents some international evidence from the literature.

In addition to convincing empirical evidence, the existence of a factor premium should be supported by a compelling economic rationale because empirical evidence could very well be the result of data mining. Kogan and Tian (2013) make this point prominently when they write: "We should place less weight on the data the models are able to match, and instead closely scrutinize the theoretical plausibility and empirical evidence in favor of or against their main economic mechanisms." Exhibit 3 summarizes the economic rationale supporting the six common factors.

Overall, the six factors — Size, Value, Momentum, Low Risk, Investment and Profitability appear to be supported both by strong empirical evidence as well as economic rationale.

EXHIBIT 1

U.S. evidence on equity factor premia.
If a monthly premium is reported in the paper, the table shows an annualized premium by calculating $(1+r)^{12}-1$ where r denotes the monthly premium. We use the "2 by 3" factors from Fama and French (2015)

Factor	Factor Definition	Period	Annual Premium	t-stat	Source
Low Risk	Stocks with low vs. high risk (beta, volatility or idiosyncratic volatility)	1926-2012	8.73%	7.12	Frazzini-Pedersen (2014)
Size	Stocks with low vs. high market cap	1926-2008	3.54%	1.62	Ang et al. (2009)
Value	Stocks with high vs. low book-to-market	1926-2008	4.53%	3.27	Ang et al. (2009)
Momentum	Stocks with high vs. low returns over past 12 months (omitting last month)	1926-2008	9.34%	5.71	Ang et al. (2009)
Profitability	Stocks with high vs. low profitability (e.g. return on equity or gross profitability)	1963-2013	3.04%	2.79	Fama-French (2014)
Investment	Stocks low vs. high investment (change in total assets)	1963-2013	4.03%	3.72	Fama-French (2014)

EXHIBIT 2

Empirical Evidence for Selected Factor Premia on Non-U.S. and Non-equity Markets

	U.S. Equities	International Equities	FCC
Value	Basu (1977); Rosenberg, Reid, Lahnstein (1985); Fama and French (1993)	Fama and French (2012)	Asness, Moskowitz, Pedersen (2013)
Momentum	Jegadeesh and Titman (1993); Carhart (1997)	Rouwenhorst (1998)	Asness, Moskowitz, Pedersen (2013)
Low Risk	Ang, Hodrick, Xing, Zhang (2006); Frazzini and Pedersen (2014)	Ang, Hodrick, Xing, Zhang (2009); Frazzini and Pedersen (2014)	Frazzini and Pedersen (2014)
Size	Banz (1981); Fama and French (1993)	Heston, Rouwenhorst, Wessels (1999); Fama and French (2012)	N.A.
Profitability	Novy-Marx (2013); Hou, Zhang, Xue (2014); Fama and French (2014)	Ammann, Odoni, Oesch (2012)	N.A.
Investment	Cooper, Gulen, Schill (2008); Hou, Zhang, Xue (2014); Fama and French (2014)	Watanabe, Xu, Yao, Yu (2013)	N.A

Designing efficient and investible proxies for risk premia

Current smart beta investment approaches only provide a partial answer to the main shortcomings of capitalization-weighted (cap-weighted) indexes. We discuss a new approach to equity investing referred to as smart factor investing. It provides an assessment of the benefits of simultaneously addressing the two main shortcomings of cap-weighted indexes, namely their undesirable factor exposures and their heavy concentration, by constructing factor indexes that explicitly seek exposures to rewarded risk factors while diversifying away unrewarded risks. Addressing these two points simultaneously is made possible through the Smart Beta 2.0 approach, which combines a stock selection step (to select stocks with the desired factor tilt or characteristics) with a diversification-based weighting scheme. This weighting scheme is applied to the relevant stock selection to obtain a well-diversified portfolio within a given factor tilt. Our results suggest that such smart factor indexes lead to considerable improvements in risk-adjusted performance.

The results in Exhibit 4 confirm that the combination of relevant security selection and appropriate weighting schemes in a two-step process leads to substantial improvements in risk-adjusted performance compared to the broad cap-weighted benchmark. The Sharpe ratio of the broad cap-weighted index is 0.41 on the long-term sample period (45 years) and the Sharpe ratio of all the factor-tilted indexes regardless of the weighting scheme chosen is higher than that of the broad cap-weighted index. This finding reasserts that the six factors carry a long-term premium, and in this sense constitute rewarded risk.

However, having a well-diversified portfolio is of equal importance to selecting the right factor tilts. Many factor index providers ignore the diversification aspect and focus solely on maximizing the factor exposures. For example, many providers follow either cap-weighting or score times market cap-weighting to construct factor indexes. However, it is well known that these weighting schemes result in concentration in few stocks which results in excess of stock level specific risks. Amenc et al. (2016) explains in detail the benefits of well-diversified factor indexes and the drawbacks of concentrated factor indexes. Shifting to the management of

specific risk exposures, we find from Exhibit 4 that even higher levels of Sharpe ratio can be achieved for each selected factor exposure through the use of a well-diversified weighting scheme known as the *diversified multi-strategy weighting scheme*[1]. The average Sharpe ratio across the six factor tilts based on diversified multi-strategy indexes is 0.56, compared to an average Sharpe ratio of 0.43 in the case of score times market cap-weighted factor tilts. This represents an increase of 30.74% in the Sharpe ratio from using the well-diversified multi-strategy weighting schemes.

The diversified multi-strategy weighting scheme is an equal-weighted combination of the following five weighting schemes — Maximum Deconcentration, Diversified Risk Weighted, Maximum Decorrelation, Efficient Minimum Volatility and Efficient Maximum Sharpe Ratio. Each weighting scheme comes with its own specific risks in addition to the stock level specific risks. As per modern portfolio theory, each investor should optimally combine risky assets so as to achieve the Maximum Sharpe Ratio (MSR) portfolio. Implementing this objective, however, is a complex task because of the presence of estimation risk for the required parameters, namely expected returns and covariance parameters. In practice, the costs of estimation error may entirely offset

EXHIBIT 3

Economic mechanisms behind main 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
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 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-sales constraints
Size	Low liquidity, high distress and downside risk is compensated by higher returns.	Limited investor attention to smaller cap stocks
Profitability	Firms facing high cost of capital will invest only in the most profitable projects	Investors do not discern high and low profitability in growth firms
Investment	Low investment reflects firms' limited scope for projects given high cost of capital	Investors under-price low investment firms due to expectation errors

EXHIBIT 4

Diversifying away unrewarded risks: performance comparison of U.S. cap-weighted factor indexes, U.S. score-times-cap-weighted factor indexes and U.S. multi-strategy factor indexes.

The analysis is based on daily total return data from December 31, 1970 to December 31, 2015 (45 years). The benchmark used for the relative analytics is the SciBeta CW US 500 index. Mid Cap, High Momentum, Low Volatility, Value, Low Investment and High Profitability selections all represent 50% of stocks with such characteristics in a U.S. universe of 500 stocks. The columns 'Score Wtd' represent the performance of corresponding factor score times market-cap weighted indexes and the columns 'Cap Wtd' represent the performance of corresponding factor cap-weighted indexes and the columns 'MultiStr' represent the performance of corresponding factor diversified multi-strategy indexes. The risk-free rate is the return of the 3-month U.S. Treasury Bill. Maximum relative drawdown is the maximum drawdown of the long/short index whose return is given by the fractional change in the ratio of the strategy index to the benchmark index. The probability of outperformance is the probability of obtaining positive excess returns from investing in the strategy for a period of 1 (or 3) years at any point during the history of the strategy. A rolling window of length 1 (or 3) years and a step size of 1 week are used. Source: www.scientificbeta.com.

U.S. Long Term (Dec 1970 – Dec 2015)	Broad CW	Mid Cap			High Momentum			Low Volatility		
		Score Wtd	Cap-Weighted	MultiStr	Score Wtd	Cap-Weighted	MultiStr	Score Wtd	Cap-Weighted	MultiStr
Ann Returns	10.45%	13.47%	12.97%	14.22%	12.47%	11.39%	13.39%	10.94%	10.76%	13.00%
Ann Volatility	16.88%	17.10%	17.09%	15.80%	18.06%	17.26%	16.01%	14.44%	15.39%	13.85%
Sharpe Ratio	0.32	0.49	0.46	0.58	0.41	0.37	0.52	0.41	0.37	0.57
Max Drawdown	54.63%	57.92%	57.09%	53.42%	52.30%	50.81%	53.25%	43.76%	51.10%	48.31%
Ann Excess Returns	-	3.02%	2.52%	3.77%	2.02%	0.94%	2.95%	0.49%	0.32%	2.55%
Ann Tracking Error	-	6.63%	5.72%	6.42%	5.34%	3.49%	4.84%	5.58%	4.27%	5.99%
1-Y Rolling TE 95%ile	-	11.69%	9.27%	11.54%	10.84%	6.24%	8.59%	12.14%	8.18%	11.38%
Information Ratio	-	0.46	0.44	0.59	0.38	0.27	0.61	0.09	0.07	0.43
Max Rel. Drawdown	-	47.99%	35.94%	42.06%	21.45%	14.44%	17.28%	37.72%	33.82%	43.46%

U.S. Long Term (Dec 1970 – Dec 2015)	Broad CW	Value			Low Investment			High Profitability		
		Score Wtd	Cap-Weighted	MultiStr	Score Wtd	Cap-Weighted	MultiStr	Score Wtd	Cap-Weighted	MultiStr
Ann Returns	10.45%	13.06%	11.90%	14.28%	12.63%	12.32%	14.01%	11.05%	10.79%	12.99%
Ann Volatility	16.88%	17.97%	17.17%	15.67%	15.93%	15.83%	14.93%	17.01%	17.02%	15.73%
Sharpe Ratio	0.32	0.44	0.40	0.59	0.47	0.46	0.60	0.35	0.34	0.50
Max Drawdown	54.63%	62.27%	60.01%	53.75%	52.05%	51.12%	50.82%	52.72%	52.29%	48.86%
Ann Excess Returns	-	2.61%	1.45%	3.84%	2.19%	1.87%	3.57%	0.60%	0.34%	2.54%
Ann Tracking Error	-	5.65%	4.42%	5.47%	4.27%	3.79%	5.42%	4.36%	3.22%	4.35%
1-Y Rolling TE 95%ile	-	9.95%	8.12%	10.03%	7.58%	6.58%	9.88%	7.44%	6.48%	7.20%
Information Ratio	-	0.46	0.33	0.70	0.51	0.49	0.66	0.14	0.11	0.58
Max Rel. Drawdown	-	20.28%	20.31%	32.68%	25.32%	26.47%	38.49%	35.91%	24.52%	25.21%

[1] *Diversified Multi-Strategy weighting is an equal-weighted combination of the following five weighting schemes — Maximum Deconcentration, Diversified Risk Weighted, Maximum Decorrelation, Efficient Minimum Volatility and Efficient Maximum Sharpe Ratio. Maximum Deconcentration consists of maximizing the effective number of stocks subject to turnover and liquidity constraints and thus corresponds to an adjusted version of equal-weighting. Diversified Risk Weighted attributes stocks weights inversely proportional to their volatility. Maximum Decorrelation constructs a portfolio of stocks that behave differently over time, which is achieved by minimizing portfolio volatility subject to the assumption that volatility is identical across stocks. Efficient Minimum Volatility consists of a volatility minimization subject to norm constraints. Efficient Maximum Sharpe ratio maximizes the Sharpe ratio of the portfolio given the assumption that expected returns are proportional to the median semi-deviation of stocks in the same decile resulting from a sort on stock-level semi-deviation. The three latter strategies require a covariance matrix as an input to the optimization problem. The covariance matrix is estimated using a robust estimation procedure employing a statistical factor model based on principal component analysis where the number of components is selected using a criterion from random matrix theory. For more details on the weighting schemes and the derivation of required input parameters, see www.scientificbeta.com).*

the benefits of optimal portfolio diversification. Similarly, an investor may be better off, for example, investing in a proxy for the global minimum variance (GMV) portfolio or the equal risk contribution (ERC) portfolio, which only require estimates for covariance parameters, as opposed to trying to estimate the MSR portfolio, which also requires expected returns estimates that are known to be noisier (Merton, 1980).

In other words, the choice in risk and return parameter estimation for efficient diversification is between "trying," which has a cost related to estimation risk (i.e., the risk of a substantial difference between the estimated parameter value and the true parameter value) or "giving up," which has a cost related to optimality risk, that is, the risk that the simplified benchmark (such as the EW or GMV portfolio) can be far from the optimal MSR benchmark. Different portfolios are intuitively expected to incur more estimation risk or more optimality risk. The parameter estimation risk of the Maximum Deconcentration weighting (which is a practical and flexible implementation of EW that reduces to EW in the absence of constraints) is zero, but it contains high optimality risk because this portfolio is optimal only in the very special case when the volatilities, expected returns and pair-wise correlations of all stocks are identical. Similarly, the Efficient MSR portfolio does not have any optimality risk, but it does entail high parameter estimation risk as one needs a reasonable estimate of expected returns, volatilities and correlations for a robust MSR optimization. Ultimately, a weighting strategy diversification approach such as that offered by ERI Scientific Beta, like in the case of multi-management, allows the risks to be diversified, except that in active management the manager's risks are more difficult to identify, and in particular, behavioral biases mean that these managers often tend to behave in the same way during extreme market phases when diversification of their management styles is most needed.

Exhibit 5 suggests that the returns of the different weighting schemes are not perfectly positively correlated, which means that further reduction of non-systematic risk can be obtained by combining different weighting schemes at the diversification stage of smart factor index construction (or equivalently by allocating to smart factor indexes that tilt towards the same factor, but that are diversified with different weighting schemes).

Thus, the Sharpe ratio of the diversified multi-strategy indexes reach even higher levels of risk-adjusted return (Sharpe ratio) than other concentrated indexes for the same factors.

These results suggest that multi-strategy factor-tilted indexes obtain the desired factor tilts without undue concentration, which provides an explanation for their superior risk-adjusted performance with respect to the cap-weighted and score times cap-weighted combination of the same selection of stocks.

Overall, it appears that the combined effects of a rewarded factor exposure ensured by a dedicated proper security selection process and efficient harvesting of the associated premium through improved portfolio diversification leads to considerable Sharpe ratio improvements compared to the broad cap-weighted index.

In a nutshell, an improved weighting scheme which focuses on diversification such as diversified multi-strategy weighting allows unrewarded risks to be diversified away. This reduction of unrewarded risk through diversification is at the heart of the Smart Beta 2.0 approach advocated by Scientific Beta.

Obtaining a well-diversified index within each factor tilt is at the core of the improved performance of these indexes. However, one may expect further benefits by allocating across different factor premia rather than focusing on a single factor tilt, notably because the academic literature and empirical research show that there is a good level of decorrelation for the risk premia associated with these factors. This allocation across different rewarded factors is at the heart of multi-smart-beta-allocation approaches, which we turn to below.

EXHIBIT 5

Average Pairwise Correlations of Excess Returns across Five Weighting Schemes.
The analysis is based on daily total returns of U.S. Long Term Track Records from December 31, 1970 to December 31, 2015. The average, minimum and maximum pairwise correlations across the five weighting schemes — Max Deconcentration, Max Decorrelation, Max Sharpe Ratio, Min Volatility and Diversified Risk Weighted for the six factors — Momentum, Low Volatility, Value, Size, Low Investment and Low Profitability are provided. Source: www.scientificbeta.com

U.S. Long Term (Dec 1970 – Dec 2015)	Diversified MultiStrategy					
	Mid Cap	High Momentum	Low Volatility	Value	Low Investment	High Profitability
Average Correlation across Five Weighting Schemes	0.89	0.87	0.96	0.88	0.90	0.85
Minimum Correlation across Five Weighting Schemes	0.76	0.68	0.91	0.75	0.78	0.64

EXHIBIT 6

Correlation of excess returns across factor tilts.
Daily total returns in USD from December 31, 1970 to December 31, 2015 are used for the U.S. Long Term universe. Correlations among all factor tilted multi-strategy indexes The universe contains 500 stocks. The full names of the multi-strategy indexes used are: SciBeta United States LTTR Mid-Cap Diversified Multi-Strategy, SciBeta United States LTTR High-Momentum Diversified Multi-Strategy, SciBeta United States LTTR Low-Volatility Diversified Multi-Strategy, SciBeta United States LTTR Value Diversified Multi-Strategy, SciBeta United States LTTR Low Investment Diversified Multi-Strategy and SciBeta United States LTTR High Profitability Diversified Multi-Strategy. Source: www.scientificbeta.com.

U.S. Long Term (Dec 1970 – Dec 2015)		Diversified MultiStrategy					
		Mid Cap	High Momentum	Low Volatility	Value	Low Investment	High Profitability
Diversified MultiStrategy	Mid Cap	1.00	0.74	0.67	0.85	0.85	0.77
	High Momentum		1.00	0.58	0.66	0.71	0.65
	Low Volatility			1.00	0.75	0.84	0.61
	Value				1.00	0.86	0.56
	Low Investment					1.00	0.70
	High Profitability						1.00

Combining multiple factors

Below, we look at Scientific Beta Six Factor Multi-Smart Factor Indexes as examples of combining different smart factor indexes. These indexes provide easy access to smart beta allocation by simply combining the different factor-tilted indexes in equal proportions or in proportion relative to their tracking error contribution.

Multi-Smart Factor Indexes draw on the diversified multi-strategy indexes for six factor tilts presented in exhibit 4 above, namely the mid cap, momentum, low volatility, value, low investment and high profitability tilts. These six factor-tilted indexes represent access to different rewarded risk factors and the associated long-term premia. However, there is extensive evidence that they may each encounter prolonged periods of underperformance. So, there is strong intuition suggesting that multi-factor allocations will tend to result in smooth outperformance and improved risk-adjusted performance. Intuitively, we would expect pronounced allocation benefits across factors which have low correlation with one another. As shown in Exhibit 6, the pairwise correlations between the relative returns of the six smart factor indexes over the cap-weighted benchmark are far below one. Importantly, this indicates that a combination of these indexes would significantly lower the overall tracking error of the portfolio relative to the cap-weighted benchmark. This is consistent with research findings in asset allocation studies. For instance, Ilmanen and Kizer (2012) have shown that factor diversification was more effective than the traditional asset-class diversification method (and that the benefits of factor diversification were still very meaningful for long-only investors).

The six factor multi-smart factor indexes, also known as Scientific Beta six factor multi-beta multi-strategy (MBMS) indexes, offer two variants of multi-factor allocations — one that allocates equally to all the six constituent smart factor indexes (Scientific Beta Multi-Beta Multi-Strategy EW) and another that allocates in proportion to their tracking error (Scientific Beta Multi-Beta Multi-Strategy ERC).

Exhibit 7 below provides performance and risk results for these multi-smart factor indexes for both U.S.A. long-term track records (43 Years) and Developed World (10 Years). It is of particular interest to compare the risk-adjusted relative performance (information ratio), relative risk and extreme relative risk of the combination to the stand-alone results obtained for each single factor tilt. In fact, while the single factor-tilted indexes all generate positive information ratios in the U.S.A. long-term track records, the results display considerable differences across factor tilts, with an information ratio (IR) of 0.46 for the low-volatility index to an IR of 0.78 for the value index. Interestingly, the Scientific Beta multi-beta multi-strategy indexes obtain IRs which are almost identical to the best result obtained among all the single factor tilts. The IR of the multi-factor combination is indeed higher than the average information ratio of the six factor-tilted indexes which make up its components. In fact, the IR of the Scientific Beta Multi-Beta Multi-Strategy indexes of 0.74, compared to the average IR of the component indexes of 0.64, corresponds to a 15.6% increase in IR. This higher IR is observed because of the reduction in tracking error. The tracking error of the Scientific Beta Multi-Beta Multi-Strategy indexes is less than that of the average of the component single factor indexes. The Scientific Beta Multi-Beta Multi-Strategy indexes reduce the tracking error on average by 15% compared to the average of the component single factor indexes. The reduction in extreme relative risk is even more significant. The Scientific Beta Multi-Beta Multi-Strategy indexes reduce the extreme tracking error on average by 19% compared to the average of the component single factor indexes. This clearly shows the allocation effect of diversifying across different factor tilts, which elevates risk-adjusted performance relative to the average result for component indexes. Similar results are obtained in the Developed World universe.

Why add two more factors?

Initially, Scientific Beta launched its first set of smart factor indexes on December 21, 2012 based on four factors — Size,

EXHIBIT 7

Performance benefits of six factor multi-beta multi-strategy indexes.
The table compares the performance and risk of the SciBeta Diversified Multi-Strategy indexes. The Scientific Beta Multi-Beta Multi-Strategy EW (ERC) index is the equal-weighted (equal relative risk contribution) combination of the six Diversified Multi-Strategy indexes with stock selection based on Mid Cap, Momentum, Low Volatility, Value, Low Investment and High Profitability respectively. All statistics are annualized and daily total returns from December 31, 1972 to December 31, 2015 in the case of USA LTTR indexes and December 31, 2005 to December 31, 2015 in the case of Developed World indexes are used for the analysis. The SciBeta CW US-500 index is used as the cap-weighted benchmark for USA LTTR indexes and the SciBeta Developed CW index is used as the cap-weighted benchmark for Developed World indexes. The yield on Secondary U.S. Treasury Bills (3M) is used as a proxy for the risk-free rate. Maximum relative drawdown is the maximum drawdown of the long/short index whose return is given by the fractional change in the ratio of the strategy index to the benchmark index. The probability of outperformance is the probability of obtaining positive excess returns from investing in the strategy for a period of 1 (or 3) years at any point during the history of the strategy. A rolling window of length 1 (or 3) years and a step size of 1 week are used. Source: www.scientificbeta.com. Scientific Beta US Long-Term Smart Factor Indexes have a 45-year track record, of which 2 years are used for calibration of parameters of MBMS ERC index. Consequently, performance is reported only for a 43-year period.

PANEL A – USA Long Term Track Records

U.S. Long-Term Track Records (Dec 1972 – Dec 2015)	USA Long-Term Cap-Weighted	Scientific Beta Diversified Multi-Strategy								
		Smart Factor Indexes							Multi-Beta Multi-Strategy (6 Factors)	
		Mid-Cap	Momentum	Low Volatility	Value	Low Investment	High Profitability	Average	Equal Weight	ERC
Ann. Returns	10.16%	14.30%	13.32%	12.94%	14.47%	14.08%	12.79%	13.65%	13.72%	13.50%
Ann. Volatility	17.15%	16.03%	16.27%	14.08%	15.90%	15.15%	15.98%	15.57%	15.34%	15.40%
Sharpe Ratio	0.29	0.57	0.50	0.56	0.59	0.59	0.48	0.55	0.56	0.54
Max. DrawDown	54.63%	53.42%	53.25%	48.31%	53.75%	50.82%	48.72%	51.38%	50.93%	50.70%
Excess Returns	-	4.14%	3.16%	2.77%	4.31%	3.92%	2.63%	3.49%	3.55%	3.34%
Tracking Error	-	6.49%	4.90%	6.08%	5.53%	5.50%	4.40%	5.48%	4.83%	4.49%
95% Tracking Error	-	11.54%	8.64%	11.43%	10.07%	9.98%	7.31%	9.83%	8.43%	7.58%
Information Ratio	-	0.64	0.64	0.46	0.78	0.71	0.60	0.64	0.74	0.74
Outperf. Prob. (3Y)	-	77.01%	76.53%	76.53%	80.17%	82.52%	82.42%	79.20%	82.04%	82.57%

PANEL B – SciBeta Developed World

SciBeta Developed (Dec 2005 – Dec 2015)	Developed Cap-Weighted	Scientific Beta Diversified Multi-Strategy								
		Smart Factor Indexes							Multi-Beta Multi-Strategy (6 Factors)	
		Mid-Cap	Momentum	Low Volatility	Value	Low Investment	High Profitability	Average	Equal Weight	ERC
Ann. Returns	5.58%	7.53%	7.19%	8.58%	6.37%	8.30%	9.03%	7.83%	7.86%	7.69%
Ann. Volatility	17.34%	16.26%	16.25%	13.98%	17.43%	15.57%	15.64%	15.86%	15.74%	16.01%
Sharpe Ratio	0.26	0.39	0.37	0.53	0.30	0.46	0.51	0.43	0.43	0.41
Max. DrawDown	57.13%	54.57%	54.35%	49.55%	57.32%	51.47%	49.98%	52.87%	52.88%	53.07%
Excess Returns	-	1.96%	1.61%	3.01%	0.80%	2.72%	3.46%	2.26%	2.29%	2.11%
Tracking Error	-	3.29%	3.69%	4.43%	2.24%	2.99%	3.19%	3.31%	2.61%	2.37%
95% Tracking Error	-	6.23%	7.24%	8.33%	3.69%	6.79%	6.55%	6.47%	5.37%	5.02%
Information Ratio	-	0.59	0.44	0.68	0.36	0.91	1.08	0.68	0.88	0.89
Outperf. Prob. (3Y)	-	89.34%	77.87%	99.45%	78.96%	100.00%	99.73%	90.89%	99.73%	100.00%

Momentum, Volatility and Value. Exhibit 8 summarizes the live performance of these smart factor indexes along with the average performance of the four indexes. The stark difference in performance evidenced over the 10-year period is also seen over the live period. The information ratio ranges from 0.46 for the Value index to 1.20 for the Low Volatility index. Subsequently, multi-smart factor indexes were launched based on these four factors.

More recently, two new factors associated with the "Quality" factor premium have been identified in the literature, namely Investment and Profitability. As seen from Exhibit 6, the two new factors are also imperfectly correlated with each other, as well as with the other four factors, thus making a strong case to include the two factors to construct the six factor multi-smart factor indexes. Adding these two factors further adds to the diversification benefits both in the long term as well as in the short term by providing a smoothed outperformance. Exhibit 9 compares the performance of six-factor and four-factor Scientific Beta Multi-Beta Multi-Strategy indexes over a 10-year period. As can be seen from exhibit 9, the information ratios of six factor Scientific Beta Multi-Beta

EXHIBIT 8

Live Track Record Performance – Developed World.
The analysis period is from December 21, 2012 to March 31, 2016. 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 Developed CW Index. The live date of the four SciBeta single factor multi-strategy indexes is December 21, 2012.

SciBeta Developed (21-Dec-2012 – 31-Mar- 2016)	Developed Cap-Weighted	Scientific Beta Diversified Multi-Strategy				
		Smart Factor Indexes				
		Mid-Cap	Momentum	Low Volatility	Value	Average
Ann. Returns	8.98%	11.65%	11.92%	12.64%	9.86%	11.52%
Ann. Volatility	11.12%	10.50%	10.80%	9.36%	10.94%	10.40%
Sharpe Ratio	0.80	1.10	1.10	1.34	0.90	1.11
Excess Returns	-	2.67%	2.94%	3.66%	0.88%	2.54%
Tracking Error	-	2.53%	2.53%	3.05%	1.92%	2.51%
Information Ratio	-	1.06	1.16	1.20	0.46	0.97

Multi-Strategy indexes are 0.88 (EW) and 0.89 (ERC) respectively, compared to the information ratios of four-factor Scientific Beta Multi-Beta Multi-Strategy indexes, which are 0.72 (EW) and 0.74 (ERC) respectively. This represents an increase of 20.42% in the information ratio of six-factor Scientific Beta Multi-Beta Multi-Strategy indexes compared to the four-factor indexes. The short-term impact of the inclusion of the two factors is clearer if we look at the year-wise outperformance of the six and four-factor Scientific Beta Multi-Beta Multi-Strategy indexes. The best excess return in each year is highlighted in green and the worst excess return in each year is highlighted in red. It is clear that the six factor Scientific Beta Multi-Beta Multi-Strategy indexes avoid the worst performance in most years because the two new factors help in smoothing out the outperformance in the short term.

To conclude, it is evident that choosing good factor tilts combined with well-diversified weighting schemes generates attractive risk-adjusted performance, and that combining the different factor tilts allows for further improvement in performance, especially relative risk-adjusted performance. Obviously, investors should thoroughly assess which factor tilts and allocation methods are most suitable to them given their investment context, beliefs and existing exposures. However, the broad six-factor index analyzed here provides broad exposure to a diversified set of strategies and factors as a useful starting point for smart beta investing. •

EXHIBIT 9

Performance benefits of six-factor Scientific Beta multi-beta multi-strategy indexes over four-factor Scientific Beta multi-beta multi-strategy indexes – Developed World.

The table compares the performance and risk of the SciBeta Diversified Multi-Strategy indexes. The four factor Scientific Beta Multi-Beta Multi-Strategy EW (ERC) index is the equal-weighted (equal relative risk contribution) combination of the four Diversified Multi-Strategy indexes with stock selection based on Mid Cap, Momentum, Low Volatility and Value whereas the six factor Scientific Beta Multi-Beta Multi-Strategy EW (ERC) index is the equal-weighted (equal relative risk contribution) combination of the six Diversified Multi-Strategy indexes with stock selection based on Mid Cap, Momentum, Low Volatility, Value , Low Investment and High Profitability respectively. All statistics are annualized and daily total returns from December 31, 2005 to December 31, 2015 are used for the analysis. The SciBeta Developed CW index is used as the cap-weighted benchmark for Developed World indexes. The yield on Secondary U.S. Treasury Bills (3M) is used as a proxy for the risk-free rate. Maximum relative drawdown is the maximum drawdown of the long/short index whose return is given by the fractional change in the ratio of the strategy index to the benchmark index. The probability of outperformance is the probability of obtaining positive excess returns from investing in the strategy for a period of 1 (or 3) years at any point during the history of the strategy. A rolling window of length 1 (or 3) years and a step size of 1 week are used. Source: www.scientificbeta.com.

PANEL – A – 10 Year Performance

SciBeta Developed (Dec 2005 – Dec 2015)	Developed Cap-Weighted	Scientific Beta USA LTTR Diversified Multi-Strategy Indexes			
		Multi-Beta Multi-Strategy (4 Factors)		Multi-Beta Multi-Strategy (6 Factors)	
		Equal Weight	ERC	Equal Weight	ERC
Ann. Returns	5.58%	7.46%	7.32%	7.86%	7.69%
Ann. Volatility	17.34%	15.85%	16.14%	15.74%	16.01%
Sharpe Ratio	0.26	0.40	0.38	0.43	0.41
Max. DrawDown	57.13%	53.94%	53.99%	52.88%	53.07%
Excess Returns	-	1.88%	1.74%	2.29%	2.11%
Tracking Error	-	2.60%	2.34%	2.61%	2.37%
95% Tracking Error	-	5.07%	4.68%	5.37%	5.02%
Information Ratio	-	0.72	0.74	0.88	0.89
Outperf. Prob. (3Y)	-	97.27%	99.73%	99.73%	100.00%

PANEL B – Yearwise Relative Returns

SciBeta Developed (Dec 2005 – Dec 2015)	Scientific Beta USA LTTR Diversified Multi-Strategy Indexes			
	Multi-Beta Multi-Strategy (4 Factors)		Multi-Beta Multi-Strategy (6 Factors)	
	Equal Weight	ERC	Equal Weight	ERC
2006	4.02%	**4.15%**	3.61%	**3.50%**
2007	-2.99%	**-3.15%**	-2.33%	**-2.26%**
2008	**2.96%**	3.05%	**3.79%**	3.71%
2009	**-1.95%**	-0.87%	-0.59%	**0.05%**
2010	5.86%	**5.11%**	**6.26%**	5.47%
2011	**2.91%**	**1.80%**	2.86%	1.89%
2012	0.11%	**0.22%**	**0.10%**	0.21%
2013	**0.05%**	0.12%	**0.89%**	0.88%
2014	3.07%	**2.90%**	**3.17%**	3.07%
2015	2.67%	**2.24%**	**2.80%**	2.47%

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INDEXES

Is Smart Beta Just Monkey Business? Beyond Simplistic Explanations of Smart Beta Performance

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Questioning "monkey portfolio" arguments

In the marketing of smart beta or alternative beta strategies, index providers focus primarily on the ability of these strategies to deliver outperformance over the cap-weighted (CW) benchmark. More often than not, a detailed analysis of risk exposure of these indexes and performance attribution to well-defined risk factors is not provided by index providers. The existence of so many smart beta strategies coupled with so little information on their performance and risk attribution could be a source of confusion, and carries a risk of leading to overgeneralization of performance drivers of these strategies.

Indeed, various authors have provided a very simple explanation of the performance of smart beta strategies. Arnott et al. (2013) claim that smart beta "necessarily results in value and size tilts, regardless of the weighting method chosen" and conclude that performance is "independent of the investment philosophies that drive the product design." Likewise, Hsu et al. (2012) write that "Outwardly different smart betas produce nearly similar premiums for similar reasons."

The argument that all smart beta strategies lead to all but identical performance and risk factor exposures is further supported by two claims. First, it is argued that "strategies premised on seemingly sensible investment beliefs … add the same or more value when inverted" (Brightman (2013)). Secondly, it is argued that smart beta strategies "add value, like Malkiel's monkey" (Brightman (2013)), because their performance is similar to randomly generated portfolios also termed "monkey portfolios."

In this article, we report results from Amenc et al. (2016a) to a series of straightforward tests of these claims. In order to test the various claims, we distinguish the three main claims made by monkey portfolio proponents:

i) All smart betas have unavoidable value and small-cap tilts resulting in performance that is similar across strategies.
ii) Smart beta strategies are as good as inverse or "up side-down" strategies.
iii) Smart beta strategy performance is driven by the "re balancing effect."

It should be noted that the potentially severe shortcomings of cap-weighted indexes, which may be exposed to high levels of concentration and poor exposure to rewarded factors, suggest that many strategies, even heuristic ones such as simple equal-weighting, for example, have the potential to outperform CW indexes. This is, however, different from saying that all smart beta strategies are "monkey-like" or identical to equal-weighting.

Our results are not supportive of the "monkey portfolio" argument. We find that various smart beta strategies display pronounced differences in factor exposures and performance characteristics. We also obtain a reassuring finding that inverting a portfolio strategy does not, in general, lead to the same performance as the original. Moreover, the link between popular smart beta strategies and rebalancing effects is not established in the data.

Our findings imply that analyzing smart beta performance and risks is not monkey business. For a better understanding of smart beta strategies it is crucial to analyze their construction principles, performance characteristics and risk factor exposures, including not only value and small-cap factors but a variety of other well-documented risk factors, such as momentum, low risk and possibly other risk factors.

Our set of smart beta strategies

Obviously, whether or not the abovementioned arguments hold may depend heavily on which class of strategies one includes. The authors making the monkey portfolio arguments claim that these results apply to smart beta strategies in general, so that an analysis of any choice of smart beta strategies should fulfill their claims.

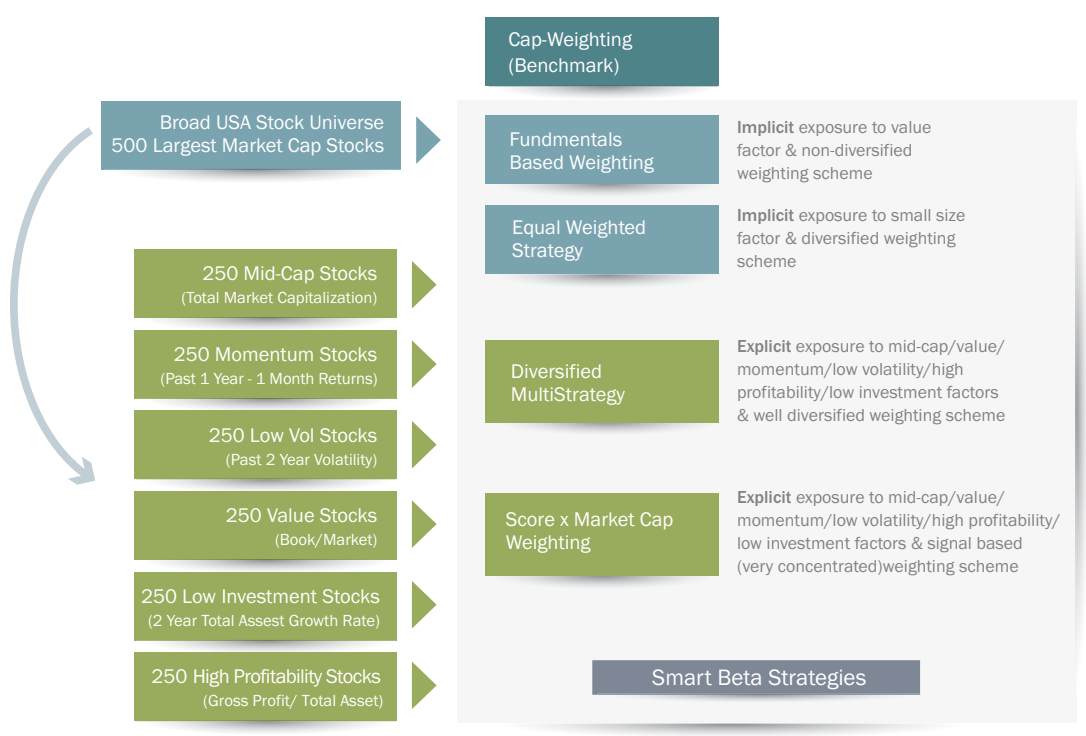
However, one may wonder whether monkey portfolio proponents have missed market developments over the past five years. In fact, the underlying analysis of this argument focuses on some broad-based Smart Beta 1.0 strategies with implicit value and size tilt. More recent products have introduced explicit tilts to various factors. Moreover, the Smart Beta 2.0 approach allows explicit tilts to be combined with diversified weighting schemes in a clear and systematic manner.

Our selection of strategies focuses mainly on explicit factor-tilted smart beta strategies, which correspond to indexes that have been launched relatively recently by providers. In fact, the first generation of smart beta indexes focused primarily on performance while paying no attention to explicitly controlling systematic risk, an approach we refer to as Smart Beta 1.0. More recently, the Smart Beta 2.0 approach proposed the idea of constructing a factor-tilted portfolio to extract the factor premia most efficiently by first explicitly selecting appropriate stocks for the desired beta and then using a diversification-based weighting scheme. This approach reconciles the diversification and de-concentration promise of alternative weighting schemes on the one hand, and factor investing on the other. Since the preliminary studies on the Smart Beta 2.0 approach (Amenc et al. (2012) and Amenc et al. (2013)), there has been an increase in smart beta offerings which have explicit factor tilts.

The increasing interest in factor-tilted smart beta indexes was also due to the success of factor investing, especially since the Norwegian Oil Fund report (Ang, Goetzmann and Schaefer (2009)), which showed that the returns relative to a cap-weighted benchmark of the fund's actively-managed portfolio can be explained by exposure to a set of well-

EXHIBIT 1

The distinction between various smart beta strategies categorized by the kind of factor exposure (implicit vs. explicit), and the kind of weighting scheme.



Since the outperformance of a smart beta strategy is neither identical across strategies nor automatic, it is important that investors consider several aspects of strategy design.

documented alternative risk factors.

Among possible strategies, we included a broad set of smart beta strategies in our tests. First, we include the popular fundamentals-weighted portfolio strategy based on a broad universe — a Smart Beta 1.0-type strategy. Given that many monkey portfolio proponents are also promoters of fundamental-weighted indexes, it is interesting to first check whether their general claims apply to the type of smart beta strategy they promote. Second, we include a variety of Smart Beta 2.0 strategies that seek explicit exposure to a given risk factor by selecting stocks with desired factor exposures, or by using a weighting that favors stocks with certain characteristics, or both. Such smart beta strategies are being offered as "factor indexes" by most major index providers. Exhibit 1 provides an overview of the nine smart beta strategies we have constructed for our tests. In addition to the broad fundamentals-weighted strategy[2], we construct factor-tilted smart beta strategies that select half the stocks in the universe to obtain the desired factor tilt and then use a diversified multi-strategy weighting scheme across index constituents[3]. In addition, we test factor-tilted smart beta strategies that use the factor scores to determine constituent weights[4] among selected stocks. Such score-weighting is employed by factor indexes from a variety of major providers. The factor tilts we consider relate to the most widely used and documented factor tilts, namely low volatility, momentum, size and value. The factor indexes are rebalanced quarterly. All strategies are applied to the U.S. large-cap stock universe (500 stocks) over a period of 40 years (Dec. 31, 1973, to Dec. 31, 2013). To avoid any hindsight bias, all parameters used in selecting and weighting the stocks are based on data observed prior to each respective rebalancing date.

Do these smart beta strategies outperform solely due to size and value loadings?

Monkey portfolio proponents argue that once we deviate from selecting stocks by their market cap and weighting them by market cap, as is done in cap-weighted market indexes, we necessarily introduce a positive value and positive size factor exposure (Chow et al. (2011)). It is argued that the same effect would occur with randomly generated portfolios, also referred to as monkey portfolios (see also Clare et al. (2013)).

In order to assess what the role of such additional factors is relative to the value and size factor, we perform regressions using a seven-factor model which uses the Betting-Against-Beta (BAB) factor from Frazzini and Pedersen (2014)[5], as well as the investment and profitability factors of Fama and French (2015) in addition to the four factors in Carhart (1997), namely the market, value, size and momentum factors.

Exhibit 2 shows that exposures of some of the smart beta strategies to factors such as momentum (MOM), BAB, investment and profitability may be large in magnitude and statistically significant. Compared to the value and size factors, these additional factors are equally important in explaining the variation in portfolio returns. For example, and as expected, the low-volatility-tilted portfolios have a pronounced exposure to the BAB factor and a low exposure to the market factor. As another example, the Momentum Diversified Multi-Strategy portfolio and Momentum Score Weighted portfolio have high MOM beta. Clearly, given these exposures, it would not make sense to claim that the returns to these low-volatility and momentum-tilted portfolios are fully explained by their size and value exposure.

Exhibit 3 shows the breakdown of excess returns of these strategies into components derived from factors and the unexplained part. The fundamental-weighted portfolio does in

EXHIBIT 2

Seven-Factor Regression.
The Market factor is the excess returns of the CRSP S&P 500 index over the risk-free rate. The yield on Secondary U.S. Treasury Bills (3M) is used as a proxy for the risk-free rate. The Size, Value, Momentum, High Profitability and Low Investment factors are obtained from the Kenneth French data library. The Betting-Against-Beta (BAB) factor is obtained from the Andrea Frazzini data library. The Newey-West (1987) estimator is used to correct for autocorrelation. Daily total returns from December 31, 1973 to December 31, 2013 are used for the analysis. Regression coefficients that have p-values less than 5% are highlighted in bold. Alphas are annualized.

Weighting Scheme	Stock Selection	Ann Alpha	Market Beta	SMB Beta	HML Beta	MOM Beta	BAB Beta	Prof Beta	Invest. Beta	R-Square
Cap Weighting (Benchmark)	ll Stocks	-	**1.00**	-	-	-	-	-	-	100.0%
Fundamentals-Based	All Stocks	-0.48%	**1.00**	**0.02**	**0.26**	**-0.04**	**0.01**	**0.04**	**0.13**	98.3%
Equal-Weighting	All Stocks	0.94%	**1.03**	**0.27**	**0.18**	**-0.10**	0.02	0.00	**0.09**	96.5%
Diversified Multi-Strategy	Mid Cap	0.54%	**1.01**	**0.42**	**0.26**	**-0.03**	**0.05**	0.03	**0.17**	91.8%
	Momentum	-0.04%	**0.98**	**0.20**	**0.09**	**0.17**	**0.06**	0.01	**0.08**	95.2%
	Low Vol	-0.78%	**0.88**	**0.10**	**0.14**	**-0.02**	**0.10**	**0.19**	**0.27**	92.8%
	Value	0.60%	**1.00**	**0.24**	**0.40**	**0.02**	**0.05**	-0.02	**0.08**	94.7%
	Low Invest.	-0.19%	**0.96**	**0.24**	**0.17**	**0.02**	**0.07**	**0.04**	**0.32**	94.4%
	High Prof.	**1.68%**	**0.95**	**0.23**	**-0.09**	**-0.03**	**0.04**	**0.08**	**0.17**	94.9%
	Multi Beta	0.32%	**0.96**	**0.24**	**0.16**	**0.02**	**0.06**	**0.06**	**0.18**	95.4%
Score x Market Cap Weighting	Mid Cap	**1.84%**	**1.06**	**0.45**	**0.26**	**-0.19**	0.01	-0.01	**0.18**	92.0%
	Momentum	0.12%	**1.02**	**0.03**	0.00	**0.40**	**-0.02**	**-0.10**	**-0.13**	96.8%
	Low Vol	**-2.36%**	**0.87**	**-0.11**	**-0.03**	**0.02**	**0.09**	**0.27**	**0.37**	94.5%
	Value	**2.34%**	**1.05**	**0.07**	**0.57**	**-0.01**	**-0.03**	**-0.19**	**-0.14**	95.7%
	Low Invest.	**-1.09%**	**0.99**	**0.06**	0.00	**0.03**	**0.03**	0.00	**0.52**	96.8%
	High Prof.	**1.56%**	**0.94**	**-0.02**	**-0.33**	**0.03**	-0.01	**0.19**	0.01	96.0%
	Multi Beta	0.46%	**0.99**	**0.08**	**0.08**	**0.05**	**0.01**	**0.03**	**0.14**	99.1%

[2] A composite fundamental weight is obtained, which is the average across four weights, each based on Current Book Value, Trailing 5-year Cash Flow, Trailing 5-year Dividend and Trailing 5-year Sales. The portfolio is rebalanced yearly on the third Friday in March.
[3] Diversified Multi-Strategy weighting is an equal weighted combination of the following five weighting schemes — Maximum Deconcentration Diversified Risk Weighted, Maximum Decorrelation, Efficient Minimum Volatility and Efficient Maximum Sharpe Ratio.
[4] Score weighting is done by weighting the stocks in proportion to their market-cap times the s-score of the respective factor. $W_i = \frac{S_i \cdot MC_i}{\sum_{k=1}^{N} S_k \cdot MC_k}$
[5] Rank-weighted portfolios that are long the 50% low market beta stocks and short the 50% high market beta stocks are constructed. Betas are estimated using the shrinkage method of Vasicek (1973) for long and short legs separately. Both long and short portfolios are rescaled to have a beta of one at portfolio formation.

fact rely mostly on exposure to the HML factor but this is not true for all strategies. Again, in particular, the low volatility and momentum-tilted portfolios, irrespective of the weighting scheme, derive a large portion of their performance from their exposure to BAB and MOM factors respectively.

Moreover, our results confirm that a fundamental equity indexation strategy does not add anything beyond exposure to well-documented factors. It is important to note that the multi-factor alpha of fundamentals-based weighting is insignificant at the 95% confidence level, which shows that no additional performance benefit exists beyond what is explained by these seven factors. It has often been claimed that in addition to the small-cap and value tilt, the so-called "rebalancing effect" — rebalancing to non-price weights — is a source of alpha for this strategy. However, the absence of alpha in the seven-factor model indicates that there is no such effect in action, at least not in the case of fundamentals-based weighting.

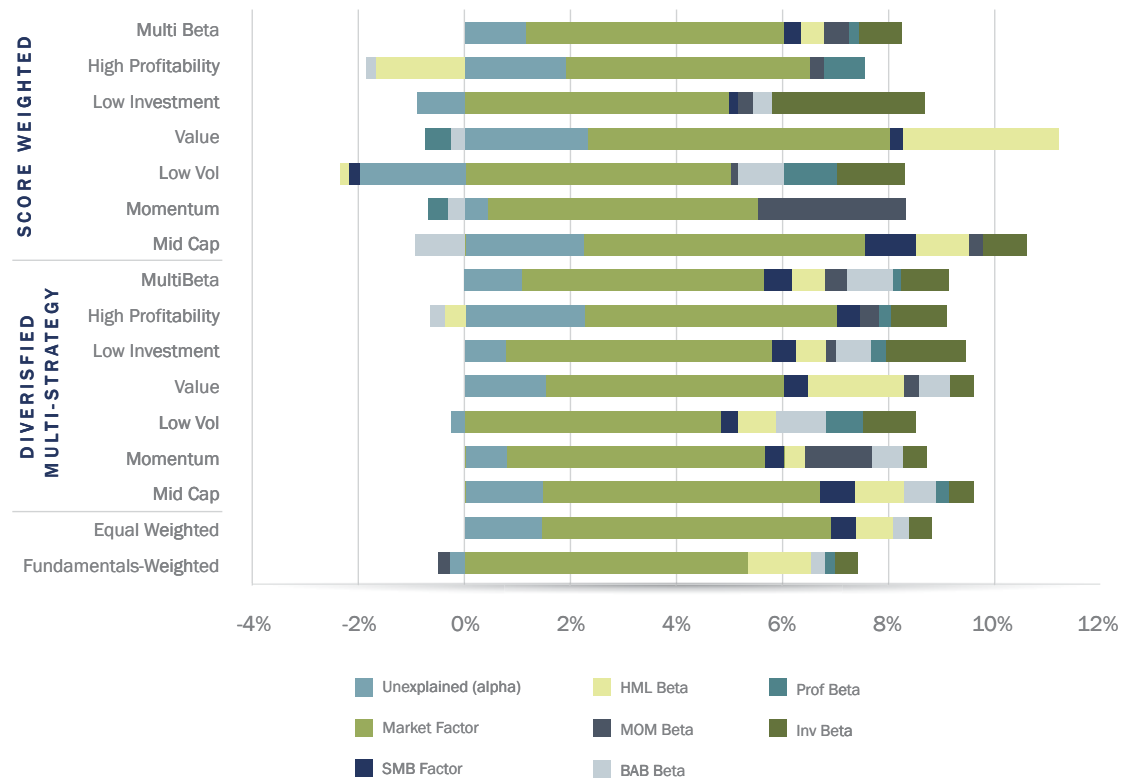
However, many of the other strategies tested go beyond value and small-cap exposure and offer pronounced exposure to additional factors. At the same time, the presence of a considerable portion of unexplained performance suggests that the portfolio construction of these indexes captures effects that cannot be explained fully by the relevant factors. Possible explanations of this unexplained part of performance are that the improved diversification scheme allows value to be added beyond the explicit factor tilts, or that yet other additional factors, which are omitted from the factor model, are at work. It should be noted that our results show quite clearly that smart beta strategies can have exposure to factors other than small size and value. This finding may not be surprising, and is fully consistent with the academic literature, which has documented the importance of various equity risk factors beyond value and small cap. In fact, it has been documented that risk-based strategies (e.g., minimum variance and equal risk contribution) take on exposures to low beta and low idiosyncratic risk factors (De Carvalho et al. (2012), Clarke et al. (2013)), and that stock portfolios seeking exposures to momentum, low-beta, investment and profitability factors generate returns that cannot be explained by the value and small-cap factors (Asness et al. (2013a), Asness et al. (2013b), Fama and French (2015)).

However, while our findings are in line with this literature, they are in stark contradiction to the claims of monkey portfolio proponents, who argue that there is nothing beyond value and small-cap exposure in smart beta strategies. Instead, our results suggest that different smart beta strategies derive performance from a varying magnitude of exposures to many different factors. These factor exposures can be managed explicitly in product design and are therefore guided by investment philosophy.

By not taking into account the different kinds of smart beta offerings available in the market, monkey portfolio proponents have produced a biased exercise based on a very specific set of strategies that may serve to prove their assertions. Moreover, the biases in selecting the strategies under analysis have not been well documented, which has led to an overgeneralization of results. Such research unfortunately provides very partial information on the characteristics of smart beta strategies.

EXHIBIT 3

Multi Factor Performance Attribution.
The Market factor is the excess returns of the CRSP S&P 500 index over risk-free rate. The yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. The Size, Value, Momentum, High Profitability, and Low Investment factors are obtained from the Kenneth French data library. The Betting-Against-Beta (BAB) factor is obtained from the Andrea Frazzini data library. The Newey-West (1987) estimator is used to correct for autocorrelation. Daily total returns from 31 December 1973to 31 December 2013 are used for the analysis.



Do these strategies add the same or more value when inverted?

The second key claim of monkey portfolio proponents is that smart beta strategies "add the same or more value when inverted" (Brightman (2013)).

First of all, we should note that whether or not a strategy behaves differently from its inverse will depend heavily on the type of strategy that one tests. Let us take the example of an equal-weighted (also known as 1/N) strategy, which is the simplest form of smart beta strategy. If one inverts its weights using the methodology in Arnott et al. (2013), one would arrive at the original portfolio (i.e., the inverse of the 1/N portfolio is the portfolio itself). Therefore, both this smart beta strategy and its inverse outperform the CW benchmark. Similarly, by using portfolios which are constrained to correspond to some optimization objective while keeping a close distance to equal-weighted portfolios, one would bias the results in favor of the claim that inverse strategies have as much merit as the original strategies.

We use the nine strategies introduced above to assess the claim that the performance of smart beta strategies remains the same or increases if their weights are inverted. To analyze this effect, we construct the inverse or upside-down portfolios for each smart beta strategy in a manner similar to that of Arnott et al. (2013).[6]

Exhibit 4 shows a basic performance comparison of portfolios and their upside-down counterparts. With the exception of the fundamental-weighted portfolio, all smart beta portfolios outperform their upside-down counterparts and they do so mostly by large margins. This is because the inverse of a factor-tilted portfolio tilts negatively towards the rewarded factor and hence does not benefit from risk premia. Therefore, investment beliefs in the form of explicit factor tilts do indeed play an important role in determining the performance of an investment strategy.

Moreover, the Sharpe ratio and information ratio of inverted portfolios is far inferior to that of the original strategies. The probability of outperformance of the original smart beta strategies is also consistently higher than that of the respective inverted portfolios. Our findings, while perfectly in line with common sense, contradict the claims made by monkey portfolio proponents.

The fundamental-weighted portfolio is the only exception because its inverse portfolio shows similar risk and returns characteristics. In appearance, the indexes termed "fundamental" are seen in our exercise to have random performance, as indicated by the term "monkey." In fact, this is due to the fact that inversion of this portfolio reduces the value beta on the one hand and increases the small size beta on the other. A similar observation can be made when inspecting the results in Arnott et al. (2013).

The rebalancing fantasy

In a smart beta strategy, rebalancing takes place at regular intervals to ensure the weights are in line with the strategy objective. This has led some to argue that[7] "it is the rebalancing that provides the outperformance" of smart beta strategies. The idea that rebalancing will automatically generate performance is related to the monkey portfolio idea that anything beats cap-weighted indexes, as long as it includes some form of rebalancing.

In fact, that any smart beta strategy would outperform

[6] The idea of turning a strategy "upside down" is to make counter bets — i.e., to overweight stocks that are underweighted in the smart beta strategy, and vice versa. Therefore, to turn factor-tilted strategy "upside down" would require the remaining half of the stock universe to be selected, and then the weights in smart beta portfolios to be inverted on this sub-universe. For example, the upside-down version of the Mid-Cap Diversified Multi-Strategy portfolio is the portfolio obtained by inverting the Large-Cap Diversified Multi-Strategy portfolio.

Let the weight of a smart beta strategy be given by W. $W = \{w_1, w_2, \ldots w_n\}$

$$w_{max} = \{w_1, w_2, \ldots w_n\}$$

The upside-down portfolio weights are given by the following expression: $W_{UD} = \{\frac{w_{max} - w_1}{n.w_{max} - 1}, \frac{w_{max} - w_2}{n.w_{max} - 1}, \ldots \frac{w_{max} - w_n}{n.w_{max} - 1}\}$

Similarly, the upside-down version of the Mid-Cap Score-Weighted portfolio is the portfolio obtained by inverting the size scores of large cap stocks such that larger stocks have higher s-scores. $S_i' = \max(S_1, S_2, \ldots S_n) - S_i$

These scores are then used to tilt the market cap weighted portfolio of large cap stocks as follows: $W_i = \frac{S_i' . MC_i}{\sum_{k=1}^{n} S_k' . MC_k}$

[7] The Maths Professor's Smart-Alpha Sums Add Up. Financial Times. January 11, 2015

EXHIBIT 4

Performance and Risk Analysis of Upside-Down Strategies.
The probability of outperformance is the probability of obtaining positive excess return returns from investing in the strategy for a period of 3 years at any point during the history of the strategy. All statistics are annualized and daily total returns from December 31, 1973 to December 31, 2013 are used for the analysis. The CRSP S&P 500 index is used as the cap-weighted benchmark. Yield on Secondary U.S. Treasury Bills (3M) is used as a proxy for the risk-free rate. Upside down strategies refer to the "Type 1"inverse in Amenc et al. (2016a).

Stock Selection	Weighting Scheme	Ann Returns	Ann Volatility	Sharpe Ratio	Ann Rel. Returns	Ann Trk Error	Information Ratio	Outperf. Prob (3Y)
All Stocks	Fundamental Wtd	12.51%	16.84%	0.43	1.56%	3.58%	0.44	69.5%
All Stocks	*Upside-down*	12.62%	17.21%	0.42	1.67%	4.08%	0.41	67.0%
Mid Cap	Div Multi-Strategy	15.67%	16.69%	0.62	4.72%	6.65%	0.71	74.7%
Large Cap	*Upside-down*	12.11%	18.10%	0.38	1.16%	3.45%	0.34	63.8%
High Momentum	Div Multi-Strategy	14.57%	16.26%	0.57	3.62%	4.83%	0.75	84.5%
Low Momentum	*Upside-down*	12.53%	19.68%	0.37	1.58%	7.99%	0.20	59.3%
Low Volatility	Div Multi-Strategy	13.90%	14.34%	0.60	2.95%	6.13%	0.48	76.4%
High Volatility	*Upside-down*	13.06%	21.31%	0.36	2.11%	7.77%	0.27	61.6%
Value	Div Multi-Strategy	15.70%	16.51%	0.63	4.75%	5.74%	0.83	78.8%
Growth	*Upside-down*	11.61%	18.47%	0.34	0.66%	4.82%	0.14	49.2%
Low Investment	Div Multi-Strategy	15.18%	15.50%	0.64	4.23%	5.61%	0.75	81.2%
High Investment	*Upside-down*	12.00%	19.40%	0.34	1.05%	5.58%	0.19	56.3%
Hi Profitability	Div Multi-Strategy	14.31%	16.13%	0.56	3.36%	4.48%	0.75	82.4%
Low Profitability	*Upside-down*	13.02%	19.12%	0.40	2.07%	6.91%	0.30	59.8%
Mid Cap	Mid Cap Score Wtd	15.40%	18.34%	0.55	4.45%	7.40%	0.60	68.9%
Large Cap	*Upside-down*	9.91%	17.80%	0.26	-1.04%	2.72%	-0.38	28.3%
High Momentum	Momentum Score Wtd	12.91%	18.35%	0.41	1.96%	5.69%	0.34	79.9%
Low Momentum	*Upside-down*	8.10%	21.15%	0.13	-2.85%	9.04%	-0.32	21.0%

automatically because of a "rebalancing return" is inconsistent with the academic finance literature. Empirical research has shown that rebalancing effects are highly dependent on the time horizon. There is ample evidence not only of return reversal effects, but also of return continuation effects (Jegadeesh and Titman (1993)). More recently, Plyakha, Uppal and Vilkov (2012) show that rebalancing effects only occur at a frequency which is much higher than typical index rebalancing frequencies. This is the reason that standard asset pricing models of Fama and French (1993, 2015) and Carhart (1997) do not include any rebalancing factor.

Nevertheless, below we provide an assessment using a model that contains, in addition to SMB and HML factors, simple long- and short-term reversal factors, since according to Arnott and West (2009), "at its heart, rebalancing is a simple contrarian strategy." Both reversal factors are obtained from the Kenneth French data library. The short-term reversal factor is a portfolio that is long the last 20-days loser stocks and short the last 20-days winner stocks. The long-term reversal factor is a portfolio that is long the last 1,250-days minus the most recent 250-days loser stocks and short the last 1,250-days minus the most recent 250-days winner stocks.

Exhibit 5 shows that all strategies have insignificant or slightly negative exposure to the short-term reversal factor. Conceptually, an intuitive requirement to benefit from the long-term reversal effect is that the portfolio must be rebalanced to fixed weights to make sure that it sells winner stocks and buys loser stocks. This is not the case with Diversified Multi-Strategy, where the stock weights are determined by combining strategies which may depend on an optimizer that relies on the information on stock correlations. Therefore, the positive exposure to long-term reversal factors of these strategies may only be due to the fact that the long-term reversal factor exposure may pick up some of the return variability which is truly attributable to the missing factors such as the low-risk, low investment and high profitability factors. Furthermore, the presence of high positive alphas in the case of factor-tilted portfolios shows that SMB, HML and reversal factors do not completely explain the variation of these portfolios' returns.

The fundamentals-based weighted portfolio, on the other hand, exhibits only positive HML beta, no SMB beta, and a negative short-term reversal beta, coupled with insignificant alpha. This suggests that this weighting scheme does not result in exposure to any reversal factors and in fact only benefits from its exposure to the HML factor. Similarly, the equal-weighted portfolio returns can be fully explained by its exposure to SMB and HML factors only, as the equal-weighted strategy has near zero exposures to both reversal factors included in the analysis.

Overall, the coefficients measuring exposure to the short-term reversal factor are mostly insignificant across the different strategies, which may not be surprising for strategies which only rebalance on a quarterly basis. The exposure to the long-term reversal factor is often significant but remains small in magnitude when compared to the magnitude of exposures to standard factors such as value and size. The empirical evidence therefore clearly does not support the claim that rebalancing would be the sole driver of smart beta performance.

Assessing smart beta strategies is not monkey business

The main arguments of the "monkey portfolio" proponents are that all smart beta strategies generate positive value and small-cap exposure similar to that generated by any random portfolio strategy, and the inverse of such strategies perform similarly or better. While we have not attempted to conduct an exhaustive assessment of these claims across all possible strategies, our analysis of some commonly employed smart beta strategies suggests that these statements are false. Our results show that while some strategies, such as fundamental equity indexation, are indeed almost solely driven by a value tilt and generate similar performance to their upside-down counterpart, many smart beta strategies display exposure to additional factors, as well as pronounced differences in factor exposures across different strategies. Moreover, and perhaps reassuringly, the inverse of these strategies generates lower performance.

Our findings of important differences across various smart beta strategies imply that care must be taken not to fall into the trap of over-simplification and over-generalization. The differences in factor exposures across smart beta strategies imply that using a particular set of indexes corresponds to particular factor selection and factor allocation decisions. Moreover, the different factor tilts play an important role in shaping the risk-return profile of smart beta strategies. Factor-tilted smart beta strategies perform due to large positive exposure to their respective factors, while their inverted counterparts underperform the originals due to less pronounced or negative exposure to the same factors.

Our results suggest that when considering the adoption of smart beta strategies, investors should carefully consider the differences across strategies. In particular, investors may require thorough due diligence on several aspects of smart beta strategies which relate to the sources of their outperformance. In fact, the potential relevance of various factors in smart beta strategies suggests that a careful assessment of factor exposures of a strategy, including but not limited to value and size, is important. Investors need to consider which set of factor exposures is best-aligned with their investment beliefs and objectives.

Moreover, beyond implementing a simple tilt to a rewarded risk factor, smart beta strategies may use two different approaches to improve risk-adjusted investment outcomes without being related to true alpha in the sense of added-value of active management.

First, smart beta strategies may aim to provide better diversification for a given factor tilt. Indeed, it is consistent with asset pricing models that expected returns depend linearly on the exposure to a given risk factor. Thus, one could simply aim to maximize exposure to this factor by concentrating a portfolio in a few stocks or — if taken to the limit — in a single stock with the highest factor exposure. However, such an approach will inevitably take on unrewarded risk, notably stock-specific risk, thus leading to inferior risk-adjusted returns. Smart beta strategies may combine the benefits of tilting to rewarded factors with the benefits of constructing well-diversified portfolios. For example, Amenc et al. (2016b[8]) provide evidence that well-diversified factor-tilted portfolios lead to improved risk/return properties relative to concentrated portfolios tilting to the same factor. Such an

[8] *Amenc, N., F. Goltz, A. Lodh, S. Sivasubramanian, 2016b, Diversified versus Concentrated Factor Indices, Journal of Portfolio Management, forthcoming.*
[9] *Markowitz, H., 1952, Portfolio Selection, Journal of Finance, Vol. 7, No. 1, pp. 77-91.*

approach of building well-diversified factor indexes thus delivers improved risk-adjusted returns by avoiding taking on unrewarded risk. Such well-diversified factor-tilted portfolios consider not only the evidence from asset pricing on additional risk factors, but also take into account the insights from portfolio theory (Markowitz (1952)[9]) that diversification allows part of the risk to be canceled. The key idea of well-diversified factor tilted indexes is to access the reward associated with exposure to systematic factors while diversifying away unrewarded risk (see Amenc et al. 2014[10]).

Second, smart beta strategies may add value through factor risk allocation. Indeed, strategies that tilt to a single factor — even if they are well diversified in the sense of avoiding exposure to unrewarded risk — are somewhat limited since they ignore the potential benefits of allocating to several factors. Factor allocation approaches combine exposures to several rewarded factors. By exploiting the information on risk parameters, and notably the correlation structure across factors, such factor allocation approaches allow risk-adjusted returns to be improved relative to static exposure to a single factor, in particular when they are implemented as a dynamic strategy. Moreover, such strategies allow specific objectives to be taken into account in a given investment context, such as risk targets in terms of absolute or relative risk. Factor allocation approaches consider information on risk parameters and investor objectives but do not aim to predict the future realization of returns.

In a nutshell, since the outperformance of a smart beta strategy is neither identical across strategies nor automatic, it is important that investors consider several aspects of strategy design. This includes the selection of factor tilts, the choice of a diversification method (for a given factor tilt), as well as the choice of a multi-factor allocation method. Selecting among smart beta strategies is not monkey business after all. •

EXHIBIT 5

Regression using Reversal Factors.
The Market factor is the excess returns of the CRSP S&P-500 index over the risk-free rate. The yield on Secondary U.S. Treasury Bills (3M) is used as a proxy for the risk-free rate. The Size, Value, Short-Term Reversal and Long-Term Reversal factors are obtained from the Kenneth French data library. The short-term reversal factor uses prior returns over the last 20 days. The long-term reversal factor uses the prior 1,250 days minus the last 250 days returns. The Newey-West (1987) estimator is used to correct for autocorrelation. Daily total returns from December 31, 1973 to December 31, 2013 are used for the analysis. Regression coefficients that have p-values of less than 5% are highlighted in bold. Alphas are annualized.

Weighting Scheme	Stock Selection	Ann Alpha	Market Beta	SMB Beta	HML Beta	Short Term Rev Beta	Long Term Rev Beta	R-Square
Cap Weighting (Benchmark)	All Stocks	-	**1.00**	-	-	-	-	100.0%
Fundamentals-Based	All Stocks	0.32%	**0.99**	0.00	**0.31**	**-0.02**	0.01	98.2%
Equal-Weighting	All Stocks	0.71%	**1.04**	**0.27**	**0.26**	-0.01	-0.01	96.1%
Diversified Multi-Strategy	Mid Cap	**1.93%**	**0.98**	**0.38**	**0.31**	-0.01	**0.06**	91.5%
	Momentum	**3.03%**	**0.93**	**0.17**	0.04	-0.01	0.04	93.3%
	Low Vol	**2.82%**	**0.81**	0.02	**0.24**	-0.02	0.01	91.0%
	Value	**1.71%**	**0.98**	**0.23**	**0.42**	0.00	0.02	94.5%
	Low Invest.	**2.53%**	**0.90**	**0.19**	**0.23**	-0.01	**0.12**	93.3%
	High Prof.	**3.20%**	**0.92**	**0.18**	**-0.05**	-0.01	**0.08**	94.7%
	Multi Beta	**2.60%**	**0.92**	**0.20**	**0.20**	-0.01	**0.05**	94.8%
Score x Market Cap Weighting	Mid Cap	0.90%	**1.07**	**0.45**	**0.40**	-0.01	0.02	90.7%
	Momentum	**2.70%**	**0.98**	**0.04**	**-0.25**	0.00	**0.12**	91.5%
	Low Vol	**2.52%**	**0.79**	**-0.23**	**0.06**	**-0.04**	**0.06**	91.6%
	Value	0.11%	**1.09**	**0.13**	**0.52**	0.01	0.03	95.2%
	Low Invest.	**1.99%**	**0.94**	0.02	**0.11**	**-0.03**	**0.16**	94.9%
	High Prof.	**3.48%**	**0.92**	**-0.09**	**-0.40**	**-0.03**	**0.12**	95.8%
	Multi Beta	**2.21%**	**0.96**	**0.05**	**0.07**	**-0.02**	**0.08**	98.9%

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INDEXES

The Drivers of Smart Beta Performance — Does Conventional Wisdom Hold?

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Smart beta strategies have been one of the strongest growth areas in investment management over the past decade. Such strategies have also drawn fierce criticism from both providers of traditional active management and those of traditional passive management. Smart beta providers are not only responding to such criticism, but have been vocal about the benefits of their respective approaches, without necessarily agreeing with each other.

Such debates have the potential to clarify the issues at hand by discussing the facts. Unfortunately, however, by often recurring to superficially convincing arguments that may not align well with the facts, such debates have also led to a number of misconceptions. Misconceptions about smart beta have arisen in different areas, such as performance drivers, investability issues and strategy design choices. Amenc et al. (2016)[11] analyze 10 common claims about smart beta and reveal the underlying misconceptions. In this article, we provide a summary of their results concerning a specific area, namely the sources of outperformance of smart beta strategies.

Misconception 1: "Smart beta generates alpha"

Smart beta aims at outperforming standard cap-weighted market indexes on a risk-adjusted basis, by obtaining a higher Sharpe ratio for example. This focus on outperformance has led some in the industry to claim that smart beta allows investors to *"find a more reliable alpha"*[12]. It is worth discussing whether equating smart beta with alpha in that way is reasonable.

Alpha is a term used to describe returns which are not explained by systematic risk exposure but rather attributable to skill.

Industry participants often equate excess return over cap-weighted indexes with alpha. This is inconsistent, however, with available knowledge on asset pricing. Indeed, in a CAPM world, excess returns over the market portfolio can only be explained by obtaining a higher beta. Thus, any strategy that beats market returns without having a higher market beta would generate an alpha, i.e., an additional amount of return which is not explained by exposure to proxies for the market factor. However, based on progress in finance that has advanced our understanding of asset pricing, it is now widely accepted that multiple factors such as value, size, momentum, etc., are priced in equity markets. This implies that a higher return can also be due to exposure to such additional risk factors. Returns which are explained by such exposures or "factor betas" are a compensation for taking on additional types of risks. Moreover, they result from following systematic strategies which are widely known and can be implemented in a mechanistic framework. In this sense, such returns are neither "unexplained" nor attributable to any form of skill.

Beyond implementing a simple tilt to a rewarded risk factor, smart beta strategies may use two different approaches to improve risk-adjusted investment outcomes without being related to true alpha in the sense of added-value of active management.

First, smart beta strategies may aim to provide better diversification for a given factor tilt. Indeed, it is consistent with asset pricing models that expected returns depend linearly on the exposure to a given risk factor. Thus, one could simply aim to maximize exposure to this factor by concentrating a portfolio in a few stocks or — if taken to the limit — in a single stock with the highest factor exposure. However, such an approach will inevitably take on unrewarded risk, notably stock-specific risk, thus leading to inferior risk-adjusted returns. Smart beta strategies may combine the benefits of tilting to rewarded factors with the benefits of constructing well-diversified portfolios. For example, Amenc et al. (2016[13]) provide evidence that well-diversified factor-tilted portfolios lead to improved risk/return properties relative to concentrated portfolios tilting to the same factor. Such an approach of building well-diversified factor indexes thus delivers improved risk-adjusted returns by avoiding taking on unrewarded risk. Such well-diversified factor-tilted portfolios consider not only the evidence from asset pricing on additional risk factors, but also take into account the insights from portfolio theory (Markowitz (1952)[14]) that diversification allows part of the risk to be canceled. The key idea of well-diversified factor tilted indexes is to access the reward associated with exposure to systematic factors while diversifying away unrewarded risk (see Amenc et al. 2014[15]). Such an approach cannot be equated with manager skill or superior information and in this sense does not constitute alpha.

Second, smart beta strategies may add value through factor risk allocation. Indeed, strategies that tilt to a single factor — even if they are well diversified in the sense of avoiding exposure to unrewarded risk — are somewhat limited since they ignore the potential benefits of allocating to several factors. Factor allocation approaches combine exposures to several rewarded factors. By exploiting the information on risk parameters, and notably the correlation structure across factors, such factor allocation approaches allow risk-adjusted returns to be improved relative to static exposure to a single factor, in particular when they are implemented as a dynamic strategy. Moreover, such strategies allow specific objectives to be taken into account in a given investment context such as risk targets in terms of absolute or relative risk. Factor allocation approaches consider information on risk parameters and investor objectives but do not aim to predict the future realization of returns. Such approaches are not related to manager skill or alpha since they draw on allocation techniques which are entirely systematic and focus on using information on risk parameters without estimating future realizations, and above all without the need to forecast future returns.

Conversely, if the objective is to employ manager skill to generate alpha, one could target two sources of alpha. A first source would be to time the exposure to rewarded factors, which implies tactical bets on the returns of long-term rewarded factors. For example, a given factor which is rewarded over the long term may underperform in any given short-term period, say a calendar year, and a manager who is skilled at predicting such short-term returns could exploit such insights to generate alpha. Factor timing decisions are thus a potential source of alpha which one can qualify as "alpha stemming from tactical allocation decisions." Moreover, a manager could try to make bets on unrewarded risks. For example, while there is no long-term reward to taking on stock-specific risk, if a manager has the capacity to predict company performance over the short run he could take on such exposures temporarily to benefit from his insights. Timing factors and identifying stock-specific opportunities is in all likelihood more of an art than a science. Both of these skills are extremely hard to find and are certainly not available from well-documented systematic smart beta strategies. If one wants to access such alpha, one needs to find a skilful manager.

In fact, smart beta strategies resemble traditional cap-weighted beta strategies in many aspects, such as high levels of transparency, relying on well-documented factors and weighting methodologies, and low fees. This resemblance is essentially due to the fact that smart beta strategies can be entirely systematic, just like cap-weighting is. As outlined above, this systematic nature nevertheless offers three distinct sources of added value, namely (i) access to additional rewarded factors beyond the market factor, (ii) improved diversification targeted at avoiding exposures to unrewarded risks, and (iii) factor risk allocation allowing information on the risk parameters of a set of factors to be exploited to construct portfolios that correspond to targeted risk objectives. These sources of added value are not alpha in the sense that they do not correspond to any capacity to generate abnormal returns by predicting future asset or factor returns beyond information that is available from market prices.

Of course, starting with a smart beta framework, it is possible to generate alpha. In the area of smart beta, the most relevant potential source of alpha is factor timing. It is obvious that this source of alpha is not accessible in the framework of systematic strategies such as those that smart beta indexes, or more generally systematic smart beta strategies, are based on. The key difference with traditional active management is also precisely this systematic nature. Common smart beta strategies require neither the rare talent of skillful active managers to be identified nor a manager to be monitored for potential risk shifting and style drift, because they do not rely on alpha. In contrast, the implementation of an alpha creation strategy is essentially the result of discretionary decisions that rarely correspond to the most common forms of smart beta, which are often expressed through the construction methodologies and the systematic rebalancing of indexes.

When evaluating purely systematic strategies, one should be careful to use an appropriate performance evaluation model. For example, even smart beta strategies which simply tilt to a given factor will deliver alpha relative to a CAPM benchmark, but this alpha is due mainly to the fact that the CAPM is a poor model that omits relevant risk factors. These factors are at the heart of smart beta and systematic factor investing. It is clear that the use of a multifactor performance attribution model allows the sources of smart beta returns to be better understood and their beta properties to be emphasized rather than emphasizing their supposed alpha, which more often than not results from poor measurement (i.e., omission) of portfolio betas. While smart beta providers may be tempted to claim that their strategies deliver alpha — in order to justify higher fees, for example — the fact that they do not is actually reassuring for users of smart beta. In fact, the existence of premia for standard factors such as value, momentum, etc., is subject to broad consensus and is well documented. The benefits of diversifying away unrewarded risk likewise constitute a pillar of finance, and are explained in any finance textbook. Finally, the benefits of risk allocation are also widely documented and draw on well-known portfolio construction and risk estimation techniques. These benefits can thus be implemented based on consensual insights and a vast amount of academic evidence.

[11] *Amenc, N., F. Goltz and J. Ulahel, 2016, Ten Misconceptions about Smart Beta, ERI Scientific Beta working paper.*
[12] *Arnott, R., and E. Kose, August 2014, What "Smart Beta" Means to Us, http://www.researchaffiliates.com/Our%20Ideas/Insights/Fundamentals/Pages/292_What_Smart_Beta_Means_to_Us.aspx*
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Misconception 2: "Anything beats cap-weighted market indexes"

Some have argued that the limitations of cap-weighted indexes are so strong that any alternative index construction, including randomly generated portfolios (so-called "monkey portfolios"), will do better. In other words, smart beta strategies supposedly "add value, like Malkiel's monkey"[16]. Consistent with this idea, it has been claimed[17] that "popular strategy indexes, when inverted, produce even better outperformance" and "the investment beliefs upon which many investment strategies are ostensibly based play little or no role in their outperformance."

Here we summarize results from Amenc et al. (2015)[18], who empirically assess the validity of such claims for a range of test portfolios. Exhibit 1 below provides an extract of some of the results where the authors invert simple factor tilted strategies which employ stock selection and score-based weighting to obtain a given factor tilt. Such strategies correspond to common offerings in the area of smart beta indexes. The exhibit provides performance statistics relative to the cap-weighted reference index for both the original strategies and the inverted strategies.

The results displayed in the table show that inverting the strategy does not only turn the weights upside down, but also changes the performance. For example, while a value-tilted strategy leads to a positive outperformance of 3.94% annualized, the inverse of this strategy leads to -2.07% returns relative to the cap-weighted reference index. Similar results hold for all other factor tilts. These results suggest that, rather than being irrelevant, the investment beliefs in the form of explicit factor tilts do indeed play an important role in determining the performance of an investment strategy.

There is a straightforward difference between the strategies analyzed in Amenc et al. (2015) and the analysis that led others to the claim that anything beats cap-weighted indexes[20]. In fact, one could easily be led to the conclusion that inverted strategies lead to similar outperformance as the original strategies when biasing the selection of strategies towards those that are similar to equal-weighting. Obviously, when inverting the weights of a strategy that is close to equal-weighting, one ends up with another strategy that is also close to equal-weighting, and thus the performance of the original and its inverse will, unsurprisingly, look similar. The analysis in Amenc et al. (2015) avoids creating such a bias towards strategies that are close to equal-weighted by including a broad set of strategies tilting to different factors and using different weighting schemes.

The findings of contrasted performance between factor-tilted strategies and their inverses contradicts the claim that anything will beat cap-weighting. Indeed, designing exposures to negatively rewarded factors (such as growth, low momentum or large cap) moves away from the cap-weighted reference index but does not lead to outperformance. Thus, rather than relying on a supposedly automatic effect that moving away from cap-weighting will deterministically improve performance, investors in smart beta strategies need to analyze the factor tilts and diversification mechanisms employed and identify which smart beta strategies correspond to their investment beliefs and objectives.

Misconception 3: "All smart beta performance comes from value and small cap exposure"

Some argue that once we deviate from selecting and weighting stocks by their market value, as is done in cap-weighted market indexes, this *"necessarily results in value and size tilts, regardless of the weighting method chosen"*[21] and these tilts suffice to explain outperformance.

While this may obviously be true for some smart beta strategies which — by design — will lead only to small-cap and value exposures, this notion is inconsistent with evidence on a wide range of smart beta strategies. In particular, Amenc, Goltz and Lodh (2015)[22] show that typical factor-tilted smart beta strategies can have exposure to factors other than small-cap and value. This finding may not be surprising, and is fully consistent with the academic literature, which has documented the importance of various equity risk factors beyond value and small cap (Leote de Carvalho, Lu and Moulin, 2012[23]; Clarke, de Silva and Thorley, 2013[24]; Asness, Moskowitz and Pedersen, 2013[25]; Asness, Frazzini and Pedersen, 2013[26]).

EXHIBIT 1

Performance of Smart Beta Strategies and their Upside-Down Strategies.
All statistics are annualized and daily total returns from December 31, 1973 to December 31, 2013 are used for the analysis. The CRSP S&P 500 index is used as the cap-weighted benchmark. The table reproduces results for a selection of "Type 1" upside-down strategies from Exhibit 6 in Amenc et al. (2015)[19].

Stock Selection	Weighting Scheme	Ann Rel. Returns	Information Ratio
Mid Cap	Mid Cap Score Wtd	4.45%	0.60
Large Cap	| *Upside-down*	-1.04%	-0.38
High Momentum	Momentum Score Wtd	1.96%	0.34
Low Momentum	| *Upside-down*	-2.85%	-0.32
Low Volatility	Low Volatility Score Wtd	0.54%	0.09
High Volatility	| *Upside-down*	-1.89%	-0.15
Value	Value Score Wtd	3.94%	0.66
Growth	| *Upside-down*	-2.07%	-0.51
Low Investment	Low Inv Score Wtd	2.31%	0.52
High Investment	| *Upside-down*	-1.80%	-0.38
High Profitability	High Prof Score Wtd	0.57%	0.12
Low Profitability	| *Upside-down*	-0.58%	-0.08

Amenc, Goltz and Lodh (2015)[27] show in particular that the Low Volatility and Momentum-tilted portfolios, irrespective of the weighting scheme, derive a large portion of their performance from their exposure to low beta and momentum factors respectively. The contributions of factors other than value and size to portfolio risk and return invalidates the claim that there is nothing beyond size and value exposure in smart beta strategies.

Moreover, they show that many smart beta strategies present a considerable portion of unexplained performance, which suggests that the portfolio construction of these indexes captures effects that cannot be explained fully by the relevant factors. Possible explanations of this unexplained part of performance are that the improved diversification scheme allows value to be added beyond the explicit factor tilts, or that yet other additional factors, which are omitted from the factor model, are at work.

However, while the findings in Amenc et al. (2015) are in line with this literature, they stand in stark contradiction to the claim that there is nothing beyond value and small-cap exposure in smart beta strategies. Instead, these results suggest that different smart beta strategies derive performance from different exposures to several factors that may go beyond size and value.

In fact, alternative weighting schemes — by deviating from standard cap-weighted indexes — may introduce implicit factor exposures (such as value and size, and potentially others). However, using alternative weighting schemes without providing any option to target factor exposures explicitly corresponds to a first-generation smart beta approach, also referred to as Smart Beta 1.0. Such approaches are rather limited as they do not allow for an explicit choice of risk factor exposures or control of such exposures but instead rely on deconcentration with respect to cap-weighted indexes, which naturally leads to the growth and large-cap bias of cap-weighted indexes being avoided, without, however, controlling the direction in which the deviations from cap-weighting go, which leads to implicit factor exposures, but also potentially to other unmanaged and undocumented risks (e.g. sector exposures). It has been documented, for example, that fundamentally weighted indexes, which constitute a particular Smart Beta 1.0 approach, lead to pronounced sector biases (notably overweighting of financial stocks and underweighting of technology stocks) which may become a main driver of short-term performance without necessarily providing an expected long-term reward (see Amenc et al. (2012[28])).

However, a Smart Beta 2.0 approach allows the issues with such uncontrolled implicit exposures to be addressed. In fact, Amenc et al. (2012[29]) show that methodological choices can be made independently for two steps in the construction of alternative equity index strategies: the constituent selection and the choice of a diversification-based weighting scheme. They show that, even though some argue that the risk and performance of diversification-based weighting schemes are solely driven by factor tilts, it is straightforward to correct such tilts through the selection of stocks with appropriate characteristics while maintaining the improvement in achieving a risk-return objective that is due to a diversification-based weighting scheme. Such a Smart Beta 2.0 approach provides controls over deviations in terms of factor exposures, which invalidates the claim that all strategies simply tilt to value and small-cap, and also goes beyond simple Smart Beta 1.0 approaches in allowing for additional flexibility and explicit risk control.

Misconception 4: "The rebalancing effect explains smart beta performance"

In a smart beta strategy, rebalancing takes place at regular intervals to ensure the weights are in line with the strategy objective. This has led some to argue that[30] "it is the rebalancing that provides the outperformance" of smart beta strategies.

To assess this claim, it is useful to look at two separate questions. A first question is whether a positive performance effect necessarily arises from rebalancing. A second question is whether smart beta strategies necessarily capture such an effect.

On the first matter, empirical research has shown that rebalancing effects are highly dependent on the time horizon. There is ample evidence not only of return reversal effects, but also of return continuation momentum effects (Jegadeesh and Titman (1993))[31]. More recently, Plyakha, Uppal and Vilkov

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[30] *The Maths Professor's Smart-Alpha Sums Add Up. Financial Times. January 11, 2015.*
[31] *Jegadeesh, N., and S. Titman. 1993. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. Journal of Finance, vol. 48, no. 1 (March): 65-91.*

(2012)[32] show that rebalancing effects only occur at a frequency which is much higher than typical index rebalancing frequencies. A recent paper by Cuthbertson, Hayley, Motson and Nitzsche (2015)[33] recognizes that there is no consensus in the literature on the existence of a positive rebalancing effect. Qian (2014)[34] provides an analysis suggesting that whether a rebalanced portfolio will outperform a buy-and-hold portfolio or underperform it will depend on the behavior of the component assets. Given this dependency of a rebalancing bonus on specific conditions, it is perhaps not surprising that that standard asset pricing models such as those of Fama and French (1993[35], 2015[36]) and Carhart (1997)[37] do not include any rebalancing factor.

The paper by Cuthbertson, Hayley, Motson and Nitzsche (2015)[38] recognizes that the rebalancing effect might or might not exist and that there is a dispute about the issue. However, more importantly, they stress that rebalancing is mostly a mechanism for replenishing diversification. They find no evidence of the "rebalancing effect" and argue that it is indeed the diversification that is the main return driver. Indeed, it is intuitive that a buy-and-hold portfolio which is never rebalanced can lead to high concentration in assets that accumulate positive outperformance over the other assets in the portfolio. To maintain a constant level of deconcentration in a portfolio that aims at naive diversification, rebalancing is required. In addition, if a portfolio is constructed using risk estimates to aim at optimal diversification, the rebalancing of weights allows updated information on risk parameters to be considered, which is indeed important in diversification strategies where one always faces a trade-off between the cost associated with turnover and the consideration of updated parameter estimates.

A second question is whether smart beta strategies gain exposure to such rebalancing effects. On this matter, it can be noted that no convincing attribution of smart beta performance to rebalancing effects has been provided to date. Given this lack of evidence, we provide an illustrative assessment below. We draw on empirical finance research which has come up with a range of "reversal" factors, which simply move out of stocks that had strong price appreciation and into stocks that had weak returns relative to the average stock, and can thus be seen as related to rebalancing effects. In particular, researchers have documented that there are positive returns to tilting to past one-month loser stocks (short-term reversal) and past five-year loser stocks (long-term reversal or contrarian) strategy. We investigate the explanatory power of such reversal factors when omitting more standard factors. In particular, we look at unexplained average returns (alpha) in a model that only includes such reversal factors in addition to the market factor, but excludes the more standard size, value and momentum factors. We attempt to capture the returns to indexes using Maximum Deconcentration weighting (adjusted equal-weighting) on different stock selections (all stocks, momentum stocks, value stocks and mid-cap stocks). The tilted stock selections correspond to the factors from a Carhart-type model. We do not include a fundamentals-based indexation strategy in this analysis as the results for such strategies are known to be highly dependent on the precise rebalancing mechanism and timing choices used. For a discussion of this issue and empirical evidence showing that even fundamentals-based strategies do not have strong exposure to reversal effects, we refer to Amenc et al. (2015[39]).

EXHIBIT 2

Performance Evaluation (Alpha Measurement) in a Model with Reversal Factors.
The results are based on daily total returns during the period from December 31, 1974 to December 31, 2014. The Market factor is the excess returns of the CRSP S&P-500 index over the risk-free rate. The yield on Secondary U.S. Treasury Bills (3M) is used as a proxy for the risk-free rate. The reversal factors are obtained from Kenneth French´s data library. Statistics are annualized. Regression coefficients significant at the 95% level are highlighted in bold.

	SciBeta Long-Term USA Maximum Deconcentration	SciBeta Long-Term USA High-Momentum Maximum Deconcentration	SciBeta Long-Term USA Value Maximum Deconcentration	SciBeta Long-Term USA Mid-Cap Maximum Deconcentration
Ann. Rel. Returns	2.56%	3.46%	4.52%	4.33%
Regression on Market Factor and Reversal Factors				
Ann. Alpha	**1.85%**	**2.68%**	**3.42%**	**3.06%**
Mkt-RF	**0.98**	**0.97**	**0.97**	**0.98**
ST Reversal Factor	0.01	0.02	0.00	0.01
LT Reversal Factor	**0.15**	**0.09**	**0.28**	**0.29**
R-squared	94.71%	93.51%	90.22%	87.45%

It is clear from these results that the different smart beta indexes show high and significant alpha even when accounting for the reversal factors. Thus, the reversal factors do not fully capture the high average returns of such strategies. This result suggests that the performance of these strategies is not primarily driven by the reversal factors and the associated rebalancing effects.

Overall, there are serious uncertainties concerning the existence of a positive performance effect from rebalancing in general. Moreover, there is no evidence suggesting that smart beta performance is mainly driven by the mechanics of rebalancing. Given these doubts on the relevance of rebalancing effects for smart beta performance, it is unreasonable to expect guaranteed outperformance of smart beta from a deterministic rebalancing effect. Instead, factor exposures and diversification properties of such strategies need to be analyzed carefully.

Towards a differentiated understanding of performance drivers

That the growth of smart beta is accompanied by intense debate is not surprising. Such debate should have the merit of furthering the understanding of potential benefits, as well as risks and possible pitfalls. In the area of smart beta investing, intense debate has, however also produced a certain number of conclusions which are seen as common wisdom even though they do not necessarily align well with the facts.

The objective of this article is to provide perspective on misconceptions about performance drivers by pointing out conceptual considerations and empirical evidence. The analysis in this article shows that, more often than not, superficially convincing claims about smart beta performance drivers stand on shaky foundations. Our analysis also shows that considering a breadth of evidence and conceptual considerations may perhaps lead to more balanced conclusions and a more nuanced understanding of smart beta performance.

Our analysis does not aim to provide a conclusion on the universal properties of all smart beta strategies. In fact, all too often, claims about performance drivers of smart beta abstract from the large variety of approaches that exist. Accounting for the differences across different strategies is necessary to avoid rushing to premature conclusions. Indeed, many of the misconceptions correspond to overgeneralizations which do not sufficiently take into account that the term "smart beta" captures a vast variety of strategies with potentially very different properties. For example, it may be correct for some smart beta strategies to say that they are solely driven by value and small-cap tilts or that they yield similar results when one inverts the strategy. However, this does not mean that such conclusions apply to all smart beta strategies. In a nutshell, our analysis cautions against oversimplification and calls for a detailed analysis of smart beta strategy performance taking into account the specific properties of the respective strategy. •

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INDEXES

Enhanced Liability-Hedging Portfolios for Institutional Investors

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Liability-driven investing and beyond: fund separation vs. fund interaction theorems

Asset-liability management (ALM) for pension funds has become relatively straightforward, in principle, within the paradigm known as liability-driven investing (LDI). In a nutshell, when extended to ALM, modern portfolio theory and the fund separation theorem unambiguously advocate that pension plans should implement the suitable combination of a liability-hedging portfolio (LHP) invested in fixed-income securities and aiming to match the risk factors impacting the value of their liabilities as well as possible, and a performance-seeking portfolio (PSP) aiming to efficiently harvest risk premia across and within risky asset classes, and most importantly, in equity markets around the globe.

When a pension fund is underfunded, pension assets are by definition insufficient to cover the liabilities, but the pension fund may in principle optimally borrow the required amount to make up for the gap between pension assets and pension liabilities and also maintain a levered investment in performance-seeking assets which may contribute to solving the funding problem without requiring exceedingly high levels of additional contributions.

While this clear separation between the search for performance and the desire to hedge liabilities is perfectly intuitive and sensible in theory, it suffers from a number of limitations in terms of real-world implementation. The main limitation is undoubtedly the presence of leverage constraints, which implies that most underfunded pension funds cannot use as much leverage as would be required to fully hedge their liabilities.[40] In practice, pension funds end up investing all their assets in a zero- or low-leverage portfolio mostly containing stocks and bonds, with a key trade-off between a dominant allocation to equities (say, a 60/40 stock/bond split), which generates attractive levels of expected returns but also implies high levels of funding ratio volatility, or a more moderate equity allocation (say, a 40/60 stock/bond split), which requires lower ALM risk budgets but correspondingly also generates lower upside potential.

In this context, the question arises of whether it would it make sense for a pension fund to hold a customized equity portfolio engineered to exhibit enhanced liability-hedging properties vs. holding a broad off-the-shelf equity index. Intuition indeed suggests that a better alignment of the PSP with respect to the liabilities would lead to an increased allocation to stocks for the same level of volatility of the funding ratio, which in turn would generate superior access to the equity risk premium.

This article extends the LDI paradigm by assessing whether LDI solutions can be enhanced by the design of performance-seeking equity benchmarks with improved liability-hedging properties. We confirm this intuition and show that improving hedging characteristics of the performance portfolio generates welfare gains unless this improvement comes at an exceedingly large opportunity cost in terms of performance, a result that we call the fund interaction theorem. While two competing effects exist in principle (a better alignment of the equity portfolio with the liabilities leads to a higher allocation to equities for the same ALM risk budget due to enhanced liability-friendliness, but it may also lead to a lower reward per dollar invested compared to a pure focus on performance), our empirical analysis actually suggests that the selection of stocks with above-average liability-hedging properties leads to both a higher degree of liability-friendliness (as expected) and also to better performance due to increased exposure to rewarded factor tilts.

In this context, we find that very substantial increases in investor welfare would come from switching from a standard off-the-shelf cap-weighted (CW) equity benchmark to an equity benchmark designed to exhibit above-average liability hedging properties. For inflation-linked liabilities, we find that the use of a minimum variance equity benchmark based on a double-sort procedure of stocks according to (high) dividend yield and (low) volatility would have generated, over the 1999-2012 period, an annualized excess return reaching 270 basis points for the same funding ratio volatility, as well as a lower funding ratio drawdown, compared to what is obtained with the use of the standard cap-weighted S&P500 index as a benchmark.

Equity benchmarks with improved liability-friendliness

We consider two alternative approaches to the definition of liability-friendliness. The first one is based on cash-flow matching capability: under this definition, liability hedging aims at finding securities whose dividend payments match the pension payments as closely as possible. The stocks which are expected to display above-average liability-friendliness in terms of cash-flow matching capacity are those that generate large and stable dividend yields.

The second definition is based on factor exposure

EXHIBIT 1

Base Case Results on Liability-Friendly Portfolios

	SELECTIONS				
	No Sel. (CW)	No Sel. (EW)	High Div Yield	High Correlation	Low Volatility
Panel A: Liability-friendliness indicators					
Tracking Error (%)	18.8	19.0 (***)	17.9 (***)	17.4 (***)	14.6
Volatility (%)	17.3	17.3 (***)	16.2 (***)	16.2 (***)	13
Correlation (%)	1.46	-0.8	1.88 (***)	7.58 (***)	7.73
Avg. Yearly Div. Yield	3.18	2.94	5.85	3.70	4.59
Panel B: Performance indicators					
Ann. Ret. (%)	10.9	13.3	13.8	14.6	13.2
Sharpe ratio	0.42 (***)	0.55	0.62 (*)	0.68 (**)	0.73 (***)
Turnover (%)	4.4	12.2	23.3	48.9	27.5
Cond. Ann. Ret.(%)	5.5	6.4	8.8	8.2	9.6
			Low Div Yield	*Low Correlation*	*High Volatility*
Panel C: Liability-friendliness indicators of opposite selections					
Tracking Error (%)			22.6 (***)	22.1 (***)	27.8 (***)
Volatility (%)			21 (***)	20.1 (***)	26.1 (***)
Correlation (%)			-1.8	-7.5 (***)	-6.7 (***)
Avg. Yearly Div. Yield			0.51	2.50	1.38
Panel D: Performance indicators of opposite selections					
Ann. Ret. (%)			11.3	12.4	10.7
Sharpe ratio			0.36 (***)	0.43 (*)	0.27 (**)
Turnover (%)			27.5	55.1	34.2
Cond. Ann. Ret.(%)			3.3	5.1	1.8

(***) denotes significance at the 1% level, (**) at the 5% level and (*) at the 10% level.

[40] *In addition to leverage constraints, the presence of* ***uncertainty about parameter values,*** *and in particular expected returns, also implies a departure from the theoretical framework, and the relative merits of various competing heuristic proxies for performance portfolios need to be empirically assessed as a function not only of their performance properties, but also of their hedging properties.*

matching. Since perfect cash-flow replication is typically difficult to achieve in practice, investors who need to hedge liabilities may choose instead to match the risk factor exposures of their assets with those of their liabilities. The objective pursued in this case is to immunize the funding ratio against variations in the risk factors that impact liabilities, and the success is measured in terms of tracking error with the liability proxy.

In this setting with a focus on risk factor matching, a stock will be said to be liability-friendly if the tracking error of the stock returns with respect to the returns on the liability proxy is low. Given the decomposition of the tracking error into two components, one that is related to the portfolio volatility and one that is related to the portfolio correlation with the liability proxy, a low tracking error can be achieved either if the volatility of the stock is low and/or if the correlation between the stock and the liability proxy is high.

Using data from the CRSP database from 1975-2012, we construct portfolios with stocks originating from the S&P 500 universe. We cast the analysis at the individual stock level, as opposed to the sector level, given the expected presence of very substantial levels of cross-sectional dispersion in interest-rate-hedging benefits across individual stocks. The portfolios are rebalanced every year in March. In the analysis, the liability proxy is computed as a constant maturity bond and its returns are computed using 15Y U.S. treasury yields. The second step of the procedure establishes the weights that are assigned to each stock. We start by considering equal weights for all stocks (no selection EW), so as to assess the benefits of the selection stage, and we additionally provide the results for the cap-weighted portfolio of all stocks (no selection CW), which is the commonly used benchmark. In order to compare the relative performance of the portfolios, we compute the following out-of-sample indicators — the tracking error and correlation with respect to the liabilities, volatility, average dividend yield, Sharpe ratio and annual turnover (see Table 1).

From the comparison between Panel A and Panel C, we conclude that the various selection procedures indeed deliver what they are designed for. In particular, the equally-weighted portfolio of the 20% stocks with the lowest volatilities has a tracking error of 14.6% with respect to our liability proxy over the sample period, while the equally-weighted portfolio of the 20% stocks with the highest volatilities is almost twice as large at 27.8%. This spectacular improvement in tracking error does not only emanate from lower portfolio volatility; it is also linked so a strong increase in correlation with the liabilities. Hence, the selection of low-volatility stocks generates a positive 7.7% correlation with the liability proxy, while a selection of high-volatility stocks generates a negative correlation of -6.7%. Intuitively, this improvement can be traced to the fact that low-volatility stocks, which tend to be low-dividend-uncertainty stocks, are the stocks that tend to be the closest approximations of fixed-income securities, and as a result, the best approximation of bond-like liabilities. In terms of correlations, the high-correlation selection ranks only second (even though close to first), with a large turnover, suggesting that empirical correlations are highly unstable. We further observe that all selections increase the Sharpe ratio as well as the turnover, compared to both the EW and CW benchmarks, and the increased liability-friendliness of the portfolios is therefore not penalized by poorer risk-adjusted performance.[41] We also confirm that the selection on dividend yields generates a statistically and economically-significant increase in this dimension with respect to the use of the standard S&P 500 index as a benchmark.

Measuring the impact on investor welfare

We also test a double-sort procedure, starting with the 200 highest dividend-yield (DY) stocks, selecting the 100 lowest-volatility stocks amongst them, and subsequently performing a minimum-variance optimization. Overall, we find that double sorts starting with DY and then low volatility generate comparable levels of factor-matching liability-friendliness (tracking error at 14.1%) with improved cash-flow-matching properties (average DY at 5.40 compared to selection purely based on volatility.

Due to the resulting improvement in liability-hedging benefits, liability-driven investors can allocate a higher fraction of their portfolios to equities without a corresponding increase in funding ratio volatility (see Table 2). For example, we find that a pension fund allocating 40% to equities on the basis of a cap-weighted equity benchmark can allocate as much as 54% to a minimum-variance portfolio of selected stocks from the aforementioned double-sort procedure for the same volatility of the funding ratio (an increased allocation which we refer to as "iso funding ratio volatility allocation").

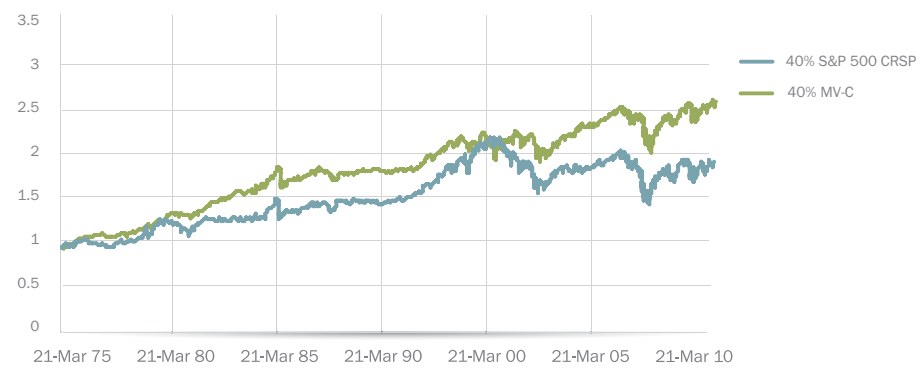
EXHIBIT 2

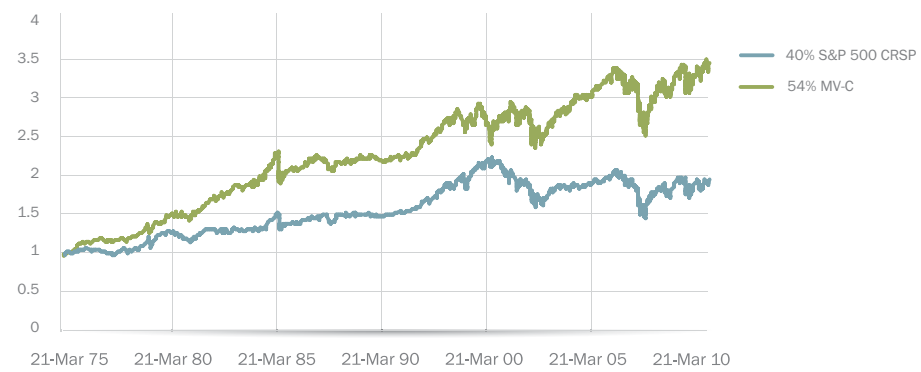
Base Case Results on Liability-Friendly Portfolios

	Equity Exposure	Volatility Funding Ratio for 40% Equity Allocation	Correlation with Liabilities	Iso Funding Ratio Volatility Equity Allocation
S&P 500	40.0%	7.0%	38.1%	
Min Variance Liability Friendly Portfolio	40.0%	5.2%	49.1%	54%

EXHIBIT 3

Historical Trajectories for the Funding Ratio





This substantial increase in equity allocation without a corresponding increase in ALM risk budgets confirms that the aforementioned improvements obtained in terms of improved liability-friendliness are economically significant.

We next disentangle the contribution to the improved funding ratio performance against the cap-weighted index (CW) for liability-friendly equity strategies (LF) into two effects: the one coming from an increased allocation to the equity block and the one coming from the performance contribution, which is generated by a higher reward per dollar invested in equities.

The resulting increase in equity allocation for the same ALM risk budget, combined with an improved risk-adjusted performance of the dedicated equity benchmark with respect to the S&P 500 index, leads to an improvement in performance reaching 180 basis points annualized over the 1975-2014 sample period. This improvement can be decomposed into a contribution purely emanating from the increase in equity allocation, assuming no impact on performance (57 basis points) and a contribution purely emanating from the improved performance of the equity benchmark, assuming no increase in allocation (123 basis points).

In terms of historical trajectories, we plot the evolution of the funding ratio over the sample period in Exhibit 3, assuming an initial funding ratio normalized at 100%.

In the top plot of Exhibit 3, where the equity allocation is set to 40%, we note that the LDI strategy based on the improved liability-friendly portfolio strongly outperforms the LDI strategy based on the S&P 500 over the sample period. In the bottom plot of Exhibit 3, we observe that the outperformance is even more spectacular when the allocation to the improved equity benchmark is adjusted to generate the same volatility of the funding ratio as when investing 40% in the S&P500 index.

CONCLUSIONS

We argue that LDI solutions can be enhanced by the design of performance-seeking equity benchmarks with improved liability-hedging properties. We show that liability-driven investors' welfare is not only increasing in the Sharpe ratio of the performance-seeking portfolio and in the correlation of the liability-hedging portfolio with the liabilities, as suggested by the fund separation theorem, but it is also increasing in the correlation between the performance-seeking portfolio and the liabilities.

The practical implication of this fund interaction theorem is that investors, such as pension funds, will by and large benefit from improving hedging characteristics of their performance-seeking portfolio, unless this improvement is associated with an exceedingly large opportunity cost in terms of risk-adjusted performance.

We report evidence of the presence of a large amount of cross-sectional dispersion in liability-hedging characteristics of individual stocks within the S&P 500 universe. In particular, we find that high-dividend-yield stocks and low-volatility stocks are more bond-like than average, and therefore exhibit enhanced liability-hedging benefits. As a result, investors with liability constraints will strongly benefit from switching their equity portfolio from a cap-weighted benchmark to a dedicated liability-friendly portfolio based on the selection of stocks which combine low volatility and high dividend yields and a constrained minimum-variance optimization.

Within the S&P 500 universe, LDI strategies switching to such a liability-friendly equity benchmark starting from a 40% allocation to S&P 500 index would benefit from a close to +1.8% per annum excess return over the 1975-2014 period without a corresponding increase in funding ratio volatility. •

[41] *In the paper, we conduct a number of robustness checks that show that these results are robust with respect to changes in the sample period, the maturity of the liability proxy, the number of stocks in the selection procedure, as well as the presence of inflation indexation in liability streams.*

INDEXES

Obtaining Attractive Exposure to Alternative Factors with Risk Allocation Strategies

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There is a growing interest amongst sophisticated asset managers and asset owners in factor investing, a disciplined approach to portfolio management that is broadly meant to allow investors to harvest risk premia across and within asset classes through liquid and cost-efficient systematic strategies without having to invest with active managers (see Ang (2014) for a comprehensive overview). While it is now well accepted that the performance of active mutual fund managers can to a large extent be replicated through a static exposure to traditional factors (see in particular Ang, Goetzmann and Schaefer (2009) analysis of the Norwegian Government Pension Fund Global), therefore implying that traditional risk premia can be most efficiently harvested in a passive manner, an outstanding question remains with respect to what is the best possible approach for harvesting alternative risk premia such as the currency carry factor or the commodity momentum factor, for example.

In a recent research project supported by Lyxor Asset Management, we attempted to analyze (i) whether systematic rules-based strategies based on investible versions of traditional and alternative factors allow for satisfactory in-sample and also out-of-sample replication of hedge fund performance, and more generally (ii) whether suitably designed risk allocation strategies may provide a cost-efficient way for investors to obtain attractive exposure to alternative factors, regardless of whether or not they can be regarded as proxies for any particular hedge fund strategy.

Hedge fund replication with traditional and alternative factors

Benchmarking hedge fund performance is particularly challenging because of the presence of numerous biases in hedge fund return databases, the most important of which are sample selection bias, survivorship bias and backfill bias. In what follows, we use EDHEC Alternative Indexes, which aggregate monthly returns on competing hedge fund indexes so as to improve the hedge fund indexes' lack of representativeness and to mitigate the bias inherent to each database (see Amenc and Martellini (2003)). We consider the following thirteen categories: Convertible Arbitrage, CTA Global, Distressed Securities, Emerging Markets, Equity Market Neutral, Event Driven, Fixed Income Arbitrage, Global Macro, Long/Short Equity, Merger Arbitrage, Relative Value, Short Selling and Fund of Funds.

The first step consists in defining a set of relevant risk factors and then finding suitable proxies. An overview of the 19 traditional and alternative risk factors considered in our empirical analysis is given in Exhibit 1. We proxy traditional risk factors by total returns of liquid and investible equity, bond, commodity and currency indexes. For alternative risk factors, we inter alia consider long/short proxies for the two most popular factors, namely value and momentum, for various asset classes, using data from Asness, Moskowitz and Pedersen (2013). A key difference between the traditional and alternative factors is that the latter cannot be regarded as directly investible, which implies that reported performance levels are likely to be overstated. Given the presence of performance biases in both hedge fund returns and alternative factor returns, we shall not focus on differences in average performance between hedge fund indexes and their replicating portfolios, and instead focus on the quality of replication measured by in-sample and out-of-sample (adjusted) R-squared.

As a first step, we perform an in-sample linear regression for each hedge fund strategy's monthly returns against a set of K factors over the whole sample period ranging from January 1997 to October 2015. For each hedge fund strategy i we have:

$$r_{t,i} = \sum_{k=1}^{K} \beta_{i,k,} f_{k,t} + e_{i,t}, \text{ with } r_{t,i}$$

being the monthly return of the hedge fund strategy at date t, $\beta_{i,k}$ the estimated OLS exposure of the monthly return on hedge fund strategy i to factor k, $f_{k,t}$ the monthly return at date t on factor k and $e_{i,t}$ the estimated specific risk in the monthly return of hedge fund index i at date t.

We estimate the explanatory power measured in terms of the regression adjusted-R-squared on the sample period in three distinct cases.

Case 1: Regression on an exhaustive set of factors (kitchen sink regression), i.e. the 19-factors set listed in Exhibit 1.

Case 2: Regression on a subset of traditional factors only (5 factors: equity, bond, credit, commodity and currency).

Case 3: Regression on a bespoke subset of a maximum of 8 economically-motivated traditional and alternative factors for each hedge fund strategy (see Exhibit 1 for the selection of factors for each hedge fund strategy).

The obtained adjusted R-squared values, reported in Exhibit 2, suggest that we can explain a substantial fraction of hedge fund strategy return variability with traditional and alternative factors, validating that a substantial part of hedge fund performance can be explained ex-post through their systematic risk exposures. The kitchen sink regression (case 1) confirms that more dynamic and/or less directional strategies such as CTA Global, Equity Market Neutral, Fixed Income Arbitrage and Merger Arbitrage strategies, with respective adjusted R-squared of 31%, 32%, 50% and 39%, are harder to replicate than more static and more directional strategies such as long/short equity or short selling, for which we obtain an adjusted R-squared of 81%.

The results we obtain also show the improvement in the explanatory power when an economically-motivated subset of factors that includes alternative factors is considered (case 3) compared to a situation where the same subset of traditional factors is used for all strategies (case 2). For example adjusted R-squared increases from 25% to 50% for Global Macro strategy and from 52% to 80% for Emerging Market strategy.

In a second step, we perform an out-of-sample hedge fund return replication exercise using the bespoke subset of factors for each strategy (case 3). The objective of this analysis is to assess whether one can capture the dynamic allocation of hedge fund strategies by explicitly allowing the betas to vary over time in a statistical model.

The out-of-sample window considered is January 1999 — October 2015, which allows us to build a "24-month rolling-window" linear clone for each strategy. For each hedge fund strategy i we have:

$$r_{t,i} = \sum_{k=1}^{K} \beta_{i,k,t} f_{k,t} + e_{i,t}.$$

Here $r_{t,i}$ is the monthly return of the hedge fund strategy i at date t, $\beta_{i,k,t}$ the estimated OLS exposure of the monthly return on hedge fund strategy i to factor k on the rolling period [t-24months; t-1], $f_{k,t}$ the monthly return at date t on factor k and $e_{i,t}$ the estimated specific risk in the monthly excess return of hedge fund i at date t.

The hedge fund clone monthly return for strategy i is:

$$r_{t,i}^{clone} = \sum_{k=1}^{K} \beta_{i,k,t} f_{k,t} + (1 - \sum_{k=1}^{K} \beta_{i,k,t}) r_{ft}.$$

Since our focus is on hedge fund replication, we take into account the possible leverage of the strategy by adding a cash component proxied by the U.S. 3-month Treasury bill index returns.

A more sophisticated approach consists in explicitly modeling dynamic risk factor exposures through state-space variables via the Kalman filter. Broadly speaking, a state-space model is defined by a transition equation and a measurement equation as follows:

$$\begin{cases} \beta_t = \beta_{t-1} + n_t & \text{(Transition equation)} \\ r_t = \beta_t \; F_t + \varepsilon_t & \text{(Measurement equation)} \end{cases}$$

where $\boldsymbol{\beta}_t$ is the vector of (unobservable) factor exposures at time t to the risk factors, $\boldsymbol{F}_t$ the vector of factor monthly returns at time t. $\boldsymbol{\eta}_t$ and ε_t are assumed to be normally distributed with a variance assumed to be constant over time. The hedge fund clone monthly return for strategy i is:

$$r_{t,i}^{clone} = \sum_{k=1}^{K} \beta_{i,k,t|\,t-1} f_{k,t} + (1 - \sum_{k=1}^{K} \beta_{i,k,t|\,t-1}) r_{ft}.$$

The substantial decrease between in-sample (see Exhibit 2) and out-of-sample (see Exhibit 3) adjusted R-squared for most of the strategies suggests that the actual replication power of the clones falls sharply when taken out of the calibration sample. For example, the Distressed Securities and Global Macro clones have out-of-sample adjusted R-squared below 30% whereas their in-sample adjusted R-squared is greater than or equal to 50%.

To get a better sense of what the out-of-sample replication quality actually is, we compute the annualized root mean squared error (RMSE, see Exhibit 3) which can be interpreted as the out-of-sample tracking error of the clone with respect to the corresponding hedge fund strategy. Our results suggest that the use of Kalman filter techniques does not systematically improve the quality of replication with respect to a simple rolling-window approach: the Kalman filter clones of the Distressed Securities, Emerging Markets, Event Driven, Global Macro, Short Selling and Fund of Funds strategies have root mean squared errors above their rolling-window clones. Overall, strategies like CTA Global or Short Selling have clones with the poorest replication quality, with root mean squared errors superior to 7.5%. Overall, these results do not support the belief that hedge fund returns can be satisfactorily replicated.

From hedge fund replication to hedge fund substitution

In this section we revisit the problem from a different perspective. Our focus is to move away from hedge fund replication, which is not per se a meaningful goal for investors anyway, and analyze whether optimized strategies based on systematic exposition to the same alternative risk factors perform better from a risk-adjusted perspective than the corresponding hedge funds or hedge fund clones. Since the same proxies for underlying alternative factor premia will be used in both the clones and the optimized portfolios, we can perform a fair comparison in terms of risk-adjusted performance in spite of the presence of performance biases in both hedge fund return and factor proxies.

EXHIBIT 1

List of risk factors

This table summarizes, in the first three columns, the whole set of traditional and alternative risk factors considered in our empirical analysis, their proxies and their sources. The other columns indicate the bespoke economic subset of factors used for each strategy in our empirical analysis. CA refers to Convertible Arbitrage, CTA to CTA Global, DS to Distressed Securities, EM to Emerging Markets, EMN to Equity Market Neutral, ED to Event Driven, FIA to Fixed Income Arbitrage, GM to Global Macro, LSE to Long Short Equity, MA to Merger Arbitrage, RV to Relative Value, SS to Short Selling, FoF to Fund of Funds.

	RISK FACTORS	PROXIES	SOURCE	CA	CTA	DS	EM	EMN	ED	FIA	GM	LSE	MA	RV	SS	FOF
TRADITIONAL FACTORS	Equity	S&P 500 TR	Bloomberg	●	●	●		●	●		●	●	●	●	●	●
	Bond	Barclays US Treasury Bond Index	Datastream	●	●	●			●	●	●			●		●
	Credit	Barclays US Corporate Inv Grade Index	Datastream	●		●			●	●	●			●		●
	Currency	US Dollar Index	Bloomberg				●									
	Commodity	S&P GSCI TR	Bloomberg		●											
	Emerging market	MSCI EM TR	MSCI Website			●	●		●		●	●		●		●
ALTERNATIVE FACTORS	Multi-Class Value	Multi-Class Global VAL	AQR website			●			●		●			●		●
	Multi-Class Momentum	Multi-Class Global MOM	AQR website			●			●		●			●		●
	Equity Defensive	Eq Global BAB	AQR website	●				●				●	●		●	
	Equity Size	Eq Global SMB	AQR website	●				●				●	●		●	
	Equity Quality	Eq Global QMJ	AQR website	●				●				●	●		●	
	Equity Value	Eq Global VAL	AQR website	●				●				●	●		●	
	Equity Momentum	Eq Global MOM	AQR website	●	●			●				●	●		●	
	FI Momentum	FI Global MOM	AQR website		●					●						
	FI Value	FI Global VAL	AQR website							●						
	FX Momentum	FX Global MOM	AQR website		●											
	FX Value	FX Global VAL	AQR website													
	Commo Momentum	COM Global MOM	AQR website		●											
	Commo Value	COM Global VAL	AQR website													

EXHIBIT 2

In-sample adjusted R-squared for empirical data.

This table reports, for each hedge fund strategy, the linear regression adjusted R-squared of its monthly returns against different sets of factors (3 cases) over the whole sample period ranging from January 1997 to October 2015.

	CA	CTA	DS	EM	EMN	ED	FIA	GM	LSE	MA	RV	SS	FoF
Case 1: 19 Factors	56	31	71	85	32	77	50	58	81	39	70	81	77
Case 2: Traditional Factors (except Emerging Market)	49	12	42	52	-2	55	35	25	64	22	55	60	46
Case 3: Economic Factors (see Exhibit 1)	54	28	52	80	16	63	28	50	71	31	56	73	68

We apply two popular robust heuristic portfolio construction methodologies, namely Equal Weight and Equal Risk Contribution, using a 24-month rolling window for each hedge fund strategy relative to its bespoke subset of economically identified risk factors for the period January 1999-October 2015. We then compare the risk-adjusted performance of rolling-window and Kalman filter clones and the corresponding optimized portfolio of the same selected factors by computing their Sharpe ratios.

The first two rows of Exhibit 4 gives the Sharpe ratios of the rolling-window and Kalman filter clones and the last two rows show the Sharpe ratios of the corresponding Equal Risk Contribution and Equal Weight optimized portfolios. The clones for Distressed Securities, Event Driven, Global Macro, Relative Value and Fund of Funds have been built with the same six risk factors: Equity, Bond, Credit, Emerging Market, Multi-Class Value and Multi-Class Momentum. The corresponding Equal Risk Contribution and Equal Weight-optimized portfolios have respective Sharpe ratios of 0.74 and 0.63, which is higher than all of the previous clones' Sharpe ratios (see, for example, the Global Macro and Distressed Securities Kalman filter clones with respective Sharpe ratios of 0.53 and 0.17).

Similarly, the Equity Market Neutral, Merger Arbitrage, Long/Short Equity and Short Selling clones have been built with the same six risk factors: Equity, Equity Defensive, Equity Size, Equity Quality, Equity Value and Equity Momentum. All the clones' Sharpe ratios are lower (see, for example, the Equity Market Neutral Kalman filter clone with Sharpe ratio of 0.74) than those of the corresponding Equal Risk Contribution and Equal Weight-optimized portfolios (respectively 1.02 and 0.96), and sometimes substantially lower (see, for example, the Merger Arbitrage and Long/Short Equity Kalman filter clones with respective Sharpe ratios of 0.39 and 0.26).

While the replication of hedge fund factor exposures appears to be a very attractive concept from a conceptual standpoint, our analysis confirms the previously documented intrinsic difficulty in achieving satisfactory out-of-sample replication power, regardless of the set of factors and the methodologies used. Our results also suggest that risk parity strategies applied to alternative risk factors could be a better alternative than hedge fund replication for harvesting alternative risk premia in an efficient way. In the end, the relevant question may not be, "Is it feasible to design accurate hedge fund clones with similar returns and lower fees?" for which the answer appears to be a clear negative, but instead, "Can suitably designed mechanical trading strategies in a number of investible factors provide a cost-efficient way for investors to harvest traditional but also alternative beta exposures?" With respect to the second question, there are reasons to believe that such low-cost alternatives to hedge funds may prove a fruitful area of investigation for asset managers and asset owners. •

The research from which this article was drawn was produced as part of the Lyxor Asset Management "Risk Allocation Solutions" research chair at EDHEC-Risk Institute.

EXHIBIT 3

Out-of-sample adjusted R-squared and annualized root mean squared error for empirical data.
This table reports, for each hedge fund strategy, the out-of-sample adjusted R-squared and the root mean squared error of the corresponding rolling-window and Kalman filter clones over the period from January 1999 to October 2015.

	HF clone Rolling-Window Out-of-Sample Adjusted R-Squared (%)	HF clone Kalman Filter Out-of-Sample Adjusted R-Squared (%)	HF Clone Rolling-Window RMSE (%)	HF Clone Kalman Filter RMSE (%)
CA	38	47	4,8	4,4
CTA	-13	8	8,5	7,6
DS	29	-1	4,9	5,8
EM	81	77	4,6	5,0
EMN	-4	-8	2,8	2,8
ED	48	20	4,0	5,0
FIA	21	31	3,3	3,1
GM	26	-23	4,0	5,2
LSE	57	58	4,6	4,5
MA	-4	20	3,2	2,8
RV	46	49	3,0	2,9
SS	74	71	7,8	8,3
FoF	60	37	3,4	4,7

EXHIBIT4

Sharpe ratios for empirical data.
This table shows, for each hedge fund strategy, the annualized Sharpe ratios (annualized return in excess of the risk-free rate divided by the annualized volatility of monthly returns) of the corresponding rolling window and Kalman filter clones and of the corresponding equal risk contribution and equal weight optimized portfolios relative to its bespoke subset of economically identified risk factors in table 1. The period considered is the out-of-sample period ranging from January 1999 to October 2015.

	HF Clone Rolling Windows	HF Clone Kalman Filter	Equal Risk Risk Contribution Portfolio	Equal Weight Portfolio
CA	0,56	0,48	1,21	1,13
CTA	0,42	0,57	0,55	0,37
DS	0,16	0,17	0,74	0,63
EM	0,39	0,30	0,25	0,40
EMN	0,47	0,74	1,02	0,96
ED	0,27	0,18	0,74	0,63
FIA	0,05	0,22	-0,25	0,37
GM	0,32	0,53	0,74	0,63
LSE	0,09	0,26	1,02	0,96
MA	0,32	0,39	1,02	0,96
RV	0,38	0,35	0,74	0,63
SS	-0,01	0,03	1,02	0,96
FoF	0,19	0,20	0,74	0,63

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Meaningful Retirement Solutions for Institutional Investors

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New challenges in retirement investing

Over the last 15 years or so, the pension fund industry has experienced a series of profound structural changes. The shift in most accounting standards towards the valuation of pension liabilities at market rates, instead of fixed discount rates, has resulted in increased volatility for pension liability portfolios (see Fabozzi et al. (2014) for a discussion of pension liability discounting rules). This new constraint has been reinforced in parallel by stricter solvency requirements that followed the 2000-2003 pension fund crisis, while ever stricter solvency requirements are also increasingly being imposed on insurance companies in the US, Europe and Asia. This evolution in accounting and prudential regulations has subsequently led a large number of corporations to close their defined-benefit pension schemes so as to reduce the impact of pension liability risk on their balance sheet and income statement. Overall, a massive shift from defined-benefit to defined-contribution pension schemes is taking place across the world.[42] Consequently, individuals are becoming increasingly responsible for making investment decisions related to their retirement financing needs, investment decisions that they are not equipped to deal with given the low levels of financial literacy within the general population and the reported inability of financial education to significantly improve upon the current situation.

In such a fast-changing environment and increasingly challenging context, the need for the investment industry to evolve beyond standard product-based market-centered approaches and to start providing both individuals with meaningful retirement investment solutions has become more obvious than ever.

From mass customization to mass production in individual money management

Currently available investment options hardly provide a satisfying answer to the retirement investment challenge, and most individuals are left with an unsatisfying choice between, on the one hand, safe annuity or variable annuity products with very limited upside potential, which will not allow them to generate the kind of target replacement income they need in retirement, and on the other hand risky strategies such as target date funds offering no security with respect to minimum levels of replacement income (see for example Bodie et al. (2010) for an analysis of the risks involved in target-date-fund investments in a retirement context).

This stands in contrast with a well-designed retirement solution that would allow individual investors to secure the kind of replacement income in retirement needed to meet their essential consumption goals, while generating a relatively high probability for them to achieve their aspirational consumption goals, with possible additional goals including health care, old age care and/or bequests.

Some dramatic changes with respect to existing investment practices are needed to facilitate the development of such meaningful retirement solutions. Just as in institutional money management, 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 meet liabilities or fulfill goals, as opposed to purely focusing on the risks impacting the market as a whole, makes standard approaches, based on balanced portfolios invested in a mixture of asset class portfolios actively and passively managed against market benchmarks, mostly inadequate.

This recognition is leading to a new investment paradigm, which has been labeled goal-based investing (GBI) in individual money management (see Chhabra (2005)), where investors' problems can be fully characterized in terms of their meaningful lifetime goals, just as liability-driven investing (LDI) has become the relevant paradigm in institutional money management, where investors' problems are broadly summarized in terms of their liabilities.

In a nutshell, goal-based investing includes two distinct elements (see Deguest et al. (2015) for a detailed analysis). On the one hand, it involves disaggregation of investor preferences into a hierarchical list of goals, with a key distinction between essential and aspirational goals, and the mapping of these groups according to hedging portfolios that possess corresponding risk characteristics. On the other hand, it involves efficient dynamic allocation to these dedicated hedging portfolios and a common performance-seeking portfolio. In this sense, the goal-based investing approach is formally consistent with the fund separation theorems that serve as founding pillars for dynamic asset pricing theory, just as was the case for the liability-driven investing approach (see also Shefrin and Statman (2000) and Das, Markowitz, Shefrin and Statman (2010) for an analysis of the relationship between modern portfolio theory portfolio optimization with mental accounts in a static setting).

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 investors' meaningful goals and associated expected shortfalls, as opposed to solely focusing on standard risk and return indicators, which are mostly irrelevant in this context.

The true start of the industrial revolution in investment management

Mass production (as in product) happened a long time ago in investment management through the introduction of mutual funds and more recently exchange-traded funds. What will trigger the true start of the industrial revolution is instead mass customization (as in customized solution), which by definition is a manufacturing and distribution technique that combines the flexibility and personalization of "custom-made" with the low unit costs associated with mass production. The true challenge is indeed to find a way to provide a large number of individual investors with meaningful dedicated investment solutions.

Within Modern Portfolio Theory, mass customization is trivialized: if investors' problems can be fully characterized by a simple risk-aversion parameter, then the aforementioned fund separation theorems state that all investors need to hold a specific combination of two common funds, one risky fund used for risk premia harvesting, and one safe (money market) fund. In reality different investors have different goals, as discussed above, and the suitable extension of the fund separation theorems implies that if the performance-seeking building block can be the same for all investors, the safe building block(s), which are known as goal-hedging portfolio(s) and are the exact counterparts in individual money management of liability-hedging portfolios in institutional money management, should be (mass) customized. Besides, the allocation to the safe vs. risky building blocks should also be engineered so as to secure investors' essential goals (e.g., minimum levels of replacement income) while generating a relatively high probability to achieve their aspirational goals (e.g., target levels of replacement income).

That mass customization is the key challenge that our industry is facing was recognized long ago, but it is only recently that we have developed the actual capacity to provide such dedicated investment solutions to individuals. This point has been made very explicitly in Merton (2003): "It is, of course, not new to say that optimal investment policy should not be 'one size fits all.' In current practice, however, there is much more uniformity in advice than is necessary with existing financial thinking and technology. That is, investment managers and advisors have a much richer set of tools available to them than they traditionally use for clients. … I see this issue as a tough engineering problem, not one of new science. We know how to approach it in principle … but actually doing it is the challenge."

Paraphrasing Robert Merton, I would like to emphasize that designing meaningful retirement solutions does not indeed require a new science. All the required ingredients are perfectly well-understood in the context of dynamic asset pricing theory (see, for example, Duffie (2001)), namely (1) a safe (goal-hedging) portfolio that should be truly safe; (2) a risky (performance-seeking) portfolio that should be well rewarded; and (3) an allocation to the risky portfolio that (3.i) reacts to changes in market conditions and (3.ii) secures investors' essential goals (EGs) while generating a high probability of reaching aspirational goals (AG).

On the other hand, scalability constraints required to address mass-customization do pose a tough engineering challenge, since it is hardly feasible to launch a customized dynamic allocation strategy for each individual investor. There are in fact two distinct dimensions of scalability, scalability with respect to the cross-sectional dimension (designing a dynamic strategy that can approximately accommodate the needs of different investors entering at the same point in time) and scalability with respect to the time-series dimension (designing a dynamic strategy that can approximately accommodate the needs of different investors entering at different points in time). The good news is that financial engineering can be used to meet these challenges (see Martellini and Milhau (2015) for a detailed analysis).

In closing, let me state that the magnitude of what is happening should not be underestimated. I do believe that our industry is truly about to experience something that looks like an industrial revolution, an industrial revolution which will take place within the next five to 10 years. We currently are at the confluence of historically powerful forces. On the one hand, liquid and transparent access to risk premia harvesting portfolios is now feasible with smart factor indexes, which are cost-efficient and scalable alternatives to active managers. On the other hand, distribution costs are bound to go down from their stratospheric levels as the trend towards disintermediation is accelerating through the development of FinTech and robo-advisor initiatives, which are putting the old business model under strong pressure, and forcing wealth management firms to entirely rethink the value that they are bringing to their clients.

In the profound soul-searching process that is currently underway in investment management, I believe it is important for all parties involved to maintain a proper perspective and see what is happening as what it actually is, namely a unique opportunity for our industry as a whole to add value to society. •

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[42] *As an example of this evolution, the number of Fortune 500 companies offering traditional DB plans to new hires fell from 51% in 1998 to 7% in 2013 (Retirement in Transition for the Fortune 500: 1998 to 2013, Insider Report, September 2014, Towers Watson, available at https://www.towerswatson.com/en/Insights/Newsletters/Americas/Insider/2014/retirement-in-transition-for-the-fortune-500-1998-to-2013).*

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