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RESEARCH FOR INSTITUTIONAL MONEY MANAGEMENT

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INTRODUCTION

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It is my pleasure to introduce the August 2015 edition of the EDHEC-Risk Institute "Research for Institutional Money Management" supplement in partnership with Pensions & Investments (P&I). Our aim with this supplement is to provide institutional investors with academic insights that are not only relevant but also of practical use from a professional perspective.

We look first at the consequences for investors of the development of passive equity investment and "smart beta" indexes. A key issue with these indexes that has not yet been resolved, and is not being attended to properly by regulators, is their level of transparency and the provision of detailed information on the indexes to investors. Even though the historical performances of these indexes are simulated for the most part, it is not possible to check the accuracy and the quality of these track records because the market does not have sufficiently detailed historical compositions and construction methodologies to be able to replicate the performances. EDHEC-Risk Institute has responded to this situation by setting up Scientific Beta, a platform that provides free access to the most detailed information possible on the risks, compositions and methodologies of thousands of smart beta indexes that are representative of the rewarded factors documented in the academic literature.

Given this reliance on the simulated historical performance of smart beta indexes, we examine the live performance of the Efficient Maximum Sharpe Ratio (MSR) indexes that EDHEC-Risk Institute has been producing with FTSE since 2009 and compare it both to smart beta indexes from other providers and EDHEC-Risk Institute's more recent index offerings within the Scientific Beta framework, which allow the Efficient MSR weighting scheme to be combined with explicit factor tilts, as well as with additional weighting schemes.

With the emergence of new factor models, discussion among researchers and practitioners has recently turned to the link between the well-known value factor on the one hand, and the profitability and investment factors on the other hand. In particular, a common question raised by investors in practice is whether value is redundant with the profitability or investment factors. Our article examines this question.

Performance analysis of systematic equity investment strategies is typically conducted on backtests that apply the smart beta methodology to historical stock returns. Concerning actual investment decisions, a relevant question therefore is how robust the outperformance is. We look at this question in terms of relative robustness and absolute robustness. A strategy is assumed to be "relatively robust" if it is able to deliver similar outperformance in similar market conditions. Absolute robustness is the capacity of the strategy to deliver risk-adjusted performance in the future to a degree that is comparable to that of the past owing to a well-understood economic mechanism rather than just by chance. We appraise the robustness of the first generations of smart beta indexes on the basis of live track records and observe that differences in live performance are due to the attention given to the design of robust weighting schemes.

We look at what investors can learn from academic research on long-term rewarded equity factors. Index providers put strong emphasis on the academic grounding of their factor indexes. It therefore seems useful to analyze what academic research has to say on equity factors to understand what we can learn from such research on designing or evaluating factor indexes. A minimum requirement for good practice in factor investing is to avoid creating a mismatch with academic factors. This can be achieved easily by referring to indicators for which academic research has provided thorough tests and economic explanations, and by refraining from proprietary "tweaks."

The objective of the following article is to compare the results of smart factor indexes with several stylized examples of concentrated factor indexes. Our conclusion is that increasing concentration leads to high turnover levels and real investibility hurdles which are not compensated by any performance advantages.

Our final article asks whether factor investing, which recommends that allocation decisions be expressed in terms of risk factors, as opposed to standard asset class decompositions, is truly a new welfare-improving investment paradigm or merely another marketing fad. The first challenge for investors who decide to express their decisions in terms of factor exposures is the identification of meaningful factors. Recent research that we have conducted as part of the Lyxor "Risk Allocation Solutions" research chair at EDHEC-Risk Institute reviews the academic literature on asset pricing and makes a list of conditions that such factors should satisfy. We then survey the empirical literature in order to identify the most consensual factors in three major asset classes, namely stocks, bonds and commodities. Empirical tests show that investible proxies for factors add value in single-class or multi-class portfolios when they are used as complements or substitutes for broad asset class indexes. Moreover, in the equity class, a portfolio of factor indexes dominates a portfolio of sector indexes.

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

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INDEXES

Nothing to Hide

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With smart beta, passive investment is experiencing a veritable revolution. Up until now, the commitment that index providers and passive managers made was to allow investors to access the average return of the market in the best economic conditions possible. This average was understood to be the performance of a cap-weighted index. In the end, passive managers or index providers, unlike active managers, were taking no reputation risk, since they were not responsible for the performance delivered to investors. It was the market.

In addition, whatever the prevailing financial climate, and notably following the various financial crises over the past 20 years, this lack of reputation risk has enabled passive managers to increase their assets under management. They were not blamed for fragile promises of outperformance or absolute performance that could not stand up to the volatility of the markets. With the appearance of smart beta, the whole promise of passive investment changes. It no longer involves performing like the market, but instead involves beating the market. In that sense, and indeed that is how smart beta is sold and how it is progressing, passive managers with smart beta make the same promise as active managers. De facto, they substitute a relative risk budget, with respect to the cap-weighted benchmark used by active managers, to the benefit of passive managers. This use of the investor's relative risk budget is based on methods and added value that used to be marketed by active investment management, whether by implementing portfolio diversification and/or exposing the portfolio to risk factors that are better rewarded than those that drive the performance of cap-weighted indexes. The success of smart beta is in fact based on two main arguments that are quite different in nature, but nonetheless complementary.

The first is that the value-creating elements that are well documented in the academic literature and are subject to consensus to the point of being supported by Nobel Prize winners, like the importance of choosing factors that are rewarded over the long term, or diversification, are often compromised by tactical bets on factors, sectors or countries, or forecasts on future stock prices made by active managers. It is this set of costly to implement and ultimately, on average, value-destroying, elements that smart beta, in its passive version, wishes to avoid by proposing, through systematic index rebalancing methodologies, to leave no room for discretionary decisions.

This argument is supported by numerous academic and empirical studies, which show that, over the long term, manager alpha that comes from tactical bets or stock picking is not persistent and that active managers underperform their benchmarks on average.

The second argument is economic. By abstaining from implementing tactical bets or stock picking, which correspond to more than 80% of investment management costs, passive smart beta investment is in a position to deliver performance at a much lower cost price.

Put together, these two arguments therefore provide the best of both worlds for the investor, since smart beta can deliver robust and inexpensive outperformance.

Unfortunately, it is clear that the industry does not really know how to take advantage of this positive paradigm today and compromises the promise of smart beta through poor practices that most often aim to attempt to offer the most attractive in-sample performances, to the detriment of their robustness[1].

As is often the case, these poor practices are hidden. On the pretext of protecting sales secrets, which can be protected by patents even though they are promoted with reference to academic research that is freely accessible, smart beta index offerings are marketed in a completely opaque manner[2].

With the exception of confidential bilateral relationships, which by definition do not improve market information, the information required to evaluate the robustness of the performance displayed by commercialized smart beta indexes is not made available to all investors or, above all, to competitors, who are those who will have most interest in criticizing their competitors' offerings. Ultimately, investors in smart beta indexes are like investors who would accept to invest in listed stocks on non-arbitraged markets, where there would be no publication of accounts, and only buyers could have confidential access to earnings reports and balance sheets.

Even though the historical performances of these indexes are simulated for the most part, it is not possible to check the accuracy and the quality of these track records because the market does not have sufficiently detailed historical compositions and construction methodologies to be able to replicate these performances.

This opacity is not called into question by the regulators, because neither the Securities and Exchange Commission, the European Commission nor IOSCO, in their regulations or proposals to improve the reliability of indexes, has advocated the application of genuine transparency, preferring to refer index providers to financial responsibilities framed by reinforcement of their governance, even though everyone knows that reinforcing governance obligations has never enabled investors to be properly protected in the past, and what is more, it does not in any way allow the risks of the indexes and the robustness of the outperformance displayed to be qualified.

Like any opaque market, that of smart beta indexes is logically faced with adverse selection phenomena. Lacking genuine transparency on the quality of the outperformance displayed, investors have no choice but to refer to the only elements that are tangible and, by definition, robust out of sample: the fees. The incentive is not to do it well, but to do it cheaper, even if this means sacrificing indispensable R&D.

In the absence of being submitted to robustness checks, which are made impossible by the opacity on the construction methods employed, the temptation is large for smart beta providers to try to improve their performance in sample, whether it involves practicing factor mining, factor fishing or model mining.

It is often the sales talent or the branding of the company that promotes "their" smart beta, rather than the quality of the smart beta, that leads to success. In that case, the assets under management raised are not relevant, because they are not the result of a decision from an informed market.

The live performances of the smart beta indexes that are the most popular and were the most commercially successful at their creation are not the best today[3]. While there is a definite connection between assets raised and performance in active investment management, this is not the case in smart beta.

It was due to these observations that EDHEC Risk Institute, a not-for-profit academic institution, set up ERI Scientific Beta at the end of 2012.

The aim of ERI Scientific Beta is to provide access, from a platform that is freely accessible to all, to the most detailed information possible on the risks, compositions and methodologies of 2,997 smart beta indexes that are representative of the rewarded factors documented in the academic literature and on their implementation within diversified indexes using methodologies that have also been the subject of numerous publications.

As part of the Smart Beta 2.0 approach[4], the www.scientificbeta.com platform also allows investors to check the impact of a change in weighting methodology, constraints and choice of factors on not only the performance and risks, but also the robustness of strategies.

The economic model of this initiative is simple. We do not charge for access to the information and merely invoice the replication support services for the indexes that are available with complete transparency on the platform. To date, the platform counts more than 17,000 users. We are proud of this success, which we hope will contribute to an improvement in the level of transparency of the smart beta market. •

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[1] *For more details on the subject of the robustness of smart beta strategies and indexes, please refer to Amenc, N., F. Goltz, A. Lodh and S. Sivasubramanian, October 2014, Robustness of Smart Beta Strategies, ERI Scientific Beta Publication.*
[2] *Very few indexes, including those that are subject to replication by UCITS or by mutual funds in the U.S., meet the requirements of transparency on historical compositions or transparency on methods. For more information, please refer to Amenc, N. and F. Ducoulombier, March 2014, Index Transparency – A Survey of European Investors' Perceptions, Needs and Expectations, EDHEC Risk Institute Publication.*
[3] *For the Developed World universe over the past five years of live performance (Dec. 31, 2009, to Dec. 31, 2014), taking MSCI World as the reference cap-weighted index, the MSCI Minimum Volatility and FTSE RAFI indexes, which are the most popular smart beta indexes in the sense of those with the largest amount of assets under management replicating them, post respective relative returns of +1.32% and -1.00%. This can be compared with a relative return of 2.09% for the FTSE EDHEC-Risk Efficient index, which corresponds to an index with one of the best levels of robustness of live performance since it was set up.*
[4] *EDHEC Risk Institute is responsible for an original smart beta index construction approach, termed "Smart Beta 2.0," which distinguishes between the choice of factors and the choice of diversification scheme, cf. Amenc, N., F. Goltz and A. Lodh. Choose Your Betas: Benchmarking Alternative Equity Index Strategies, Fall 2012, Journal of Portfolio Management. Amenc, N. and F. Goltz. Smart Beta 2.0, Winter 2013, Journal of Index Investing.*

INDEXES

Live Performance and Long-Term Track Records of ERI Scientific Beta Indexes

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The EDHEC-Risk Institute has been active in providing smart beta equity indexes since 2009. While it began by implementing Efficient Maximum Sharpe Ratio indexes through a partnership with FTSE, it has continued to expand its smart beta offerings ever since 2009, notably with the launch of its dedicated index platform, Scientific Beta, in 2013. This article looks back at the live performance of the Efficient Maximum Sharpe Ratio (MSR) indexes and compares it both to smart beta indexes from other providers and EDHEC-Risk Institute's more recent index offerings, which allow the Efficient Maximum Sharpe Ratio weighting scheme to be combined with explicit factor tilts, as well as with additional weighting schemes.

1. Live Performance and Risk of FTSE EDHEC-Risk Efficient Indexes and Comparison with U.S. Long-Term Track Records for Efficient MSR

The FTSE EDHEC-Risk Efficient Indexes use the Efficient Maximum Sharpe Ratio weighting methodology to reweight stocks in the FTSE parent index in order to improve diversification and obtain an efficient risk/reward profile of the index. This methodology is the result of research conducted by the research team at EDHEC-Risk Institute.

The observation underlying the implementation of this methodology is simple. Two outstanding portfolios exist on the efficient frontier, which represents all portfolios with the best possible return for a given level of risk. All these portfolios result from diversification termed "efficient." These two portfolios are remarkable since the first, a minimum variance portfolio, corresponds to an efficient portfolio with the smallest return, while the second, the Maximum Sharpe Ratio portfolio, has the best risk-adjusted return made possible through diversification. Traditionally, quantitative managers, and more recently smart beta index providers, have attempted to proxy the minimum variance portfolio since the calculation of the latter does not require an estimation of expected returns. An estimation of the variance-covariance matrix alone suffices to determine the efficient portfolio of minimal risk. However, in practice, these minimum variance portfolios are not always very well-diversified. The search for the minimal risk portfolio results in concentrating the portfolio in a very small number of low-volatility stocks and gives these portfolios a very defensive character (low beta portfolio) which does not enable them to take full advantage of periods when markets are rising. This concentration problem has led managers and suppliers of minimum variance or minimum volatility portfolios or indexes to use deconcentration constraints to construct the portfolios which, when they are very rigid, deteriorate significantly the performance of the latter out-of-sample. That is why EDHEC-Risk Institute is proposing, on the basis of research work[5] undertaken by one of its eminent members, Professor Raman Uppal, to introduce norm constraints that are no longer constraints on the minimum or maximum weight of the stocks but on an effective minimum number of stocks. This enables the diversification of the Scientific Beta Efficient Minimum Volatility indexes to be improved and to obtain better out-of-sample performance.

The second outstanding portfolio is the Maximum Sharpe Ratio portfolio. This portfolio is, in principle, the best portfolio in terms of risk-adjusted performance and the only one that investors should hold. However, its estimation is extremely non-robust out-of-sample as it requires the use of expected returns that cannot be estimated on the basis of past returns. To circumvent this problem, EDHEC-Risk Institute's teams have introduced the hypothesis of a positive link over the long term between the risk of stocks, measured by their semi-deviation, and their return. This hypothesis, which has been validated by extensive academic research work, ultimately enables a robust proxy of the hierarchy of stock returns to be obtained. This risk-based methodology was the subject of a major academic publication[6] and has been reflected in the index offering promoted on the Scientific Beta platform. For further details about this methodology, please refer to the corresponding white paper, "Scientific Beta Efficient Maximum Sharpe Ratio Indexes."[7]

EXHIBIT 1

Live Performance Analysis – FTSE EDHEC-Risk Efficient Indexes in Different Geographical Regions

The table shows the return and risk performance of FTSE EDHEC-Risk Efficient indexes across different geographical regions: U.S., U.K., Eurozone, Japan and Developed Asia-Pacific ex-Japan. All statistics are annualized and daily total returns from Nov. 23, 2009 to Dec. 31, 2014 are used for the analysis. Returns are in USD/GBP/EUR/JPY/USD currencies for U.S./U.K./Eurozone/Japan/Developed Asia-Pacific ex-Japan respectively. The "Secondary Market U.S. Treasury Bills (3M)" is the risk-free rate in US Dollars for U.S. and Developed Asia-Pacific ex-Japan. The "U.K. Treasury Bill Tender (3M)" is the risk-free rate in British Pounds for U.K. "Euribor (3M)" is the risk-free rate in Euros for Eurozone, and "Japan Gensaki T-Bill (1M)" is the risk-free rate in Japanese Yen for Japan. The cap-weighted benchmark is the SciBeta CW index of the corresponding universe. Source: scientificbeta.com.

Analysis Period 11/23/2009 to 12/31/2014	U.S.		U.K.		Eurozone		Japan		Developed Asia-Pacific ex-Japan	
	Broad CW	FTSE EDHEC-Risk Efficient	Broad CW	FTSE EDHEC-Risk Efficient	Broad CW	FTSE EDHEC-Risk Efficient	Broad CW	FTSE EDHEC-Risk Efficient	Broad CW	FTSE EDHEC-Risk Efficient
Ann Returns	15.22%	18.43%	8.08%	10.52%	7.16%	8.68%	12.70%	13.91%	5.75%	7.87%
Ann Volatility	15.82%	16.01%	15.53%	14.91%	19.92%	17.22%	19.84%	18.25%	18.34%	15.25%
Sharpe Ratio	0.96	1.15	0.49	0.68	0.33	0.47	0.64	0.76	0.31	0.51
Max Drawdown	18.58%	19.11%	17.12%	15.29%	30.14%	26.50%	27.81%	23.60%	31.05%	26.45%
Annual Relative Returns	-	3.21%	-	2.44%	-	1.53%	-	1.21%	-	2.12%
Tracking Error	-	2.64%	-	4.26%	-	5.01%	-	4.06%	-	5.05%
Information Ratio	-	1.21	-	0.57	-	0.30	-	0.30	-	0.42
95% Tracking Error	-	3.44%	-	5.16%	-	6.61%	-	5.14%	-	6.44%
Max Rel. Drawdown	-	4.22%	-	6.64%	-	8.51%	-	9.37%	-	6.64%

[5] *DeMiguel, V., L. Garlappi, J. Nogales and R. Uppal, 2009, A Generalized Approach to Portfolio Optimization: Improving Performance By Constraining Portfolio Norms, Management Science 55.5, 798-812.*
[6] *Amenc, N., F. Goltz, L. Martellini and P. Retkowsky, 2011, Efficient Indexation: An Alternative to Cap-Weighted Equity Indexes, Journal of Investment Management.*
[7] *Gautam, K. and A. Lodh, October 2013, Scientific Beta Efficient Maximum Sharpe Ratio Indexes, ERI Scientific Beta Publication.*

Performance of FTSE EDHEC-Risk Efficient indexes since their live date for different regions

The performance and risk statistics across the five major regions show substantial outperformance, with a great level of consistency across regions. Annual relative returns over the cap-weighted reference index range from 1.21% for Japan to 5.05% for Developed Asia-Pacific ex-Japan. For the important U.S. market, live returns of efficient indexes have exceeded those of cap-weighted indexes by more than 3% annually. It should be noted that volatility is also lower than, or similar to, that of cap-weighted indexes, leading to a pronounced increase in the Sharpe ratio, which is well in line with the objective of these indexes. Over the whole Developed region, the annual outperformance of the FTSE EDHEC-Risk Efficient index is 2.59%, with an improvement in the Sharpe Ratio of 29.29% in relation to the SciBeta Developed Cap-Weighted index.

Comparison with U.S. long-term track records from 1975 to 2014 for the Scientific Beta Efficient MSR

It is instructive to compare the results obtained over the recent live period with the long-term results, as evidenced by backtested data over 40 years. This section conducts such an analysis by juxtaposing the results for the live period of FTSE EDHEC-Risk Efficient Indexes for U.S. stocks with the backtested data for U.S. long-term track records for ERI Scientific Beta strategies that use the same weighting method, namely the Efficient Maximum Sharpe Ratio weighting scheme, and a universe of similar stocks.

The performance and risk statistics suggest that the five-year live performance shows a striking resemblance to the 40-year historical backtest. Relative annualized returns over the cap-weighted reference index are 3.21% in live data compared to 2.87% in the long-term backtest. It can therefore be concluded that the outperformance potential documented in long-term historical backtests for this method provides a reliable indication for live outperformance — even though the live performance achieved is slightly underestimated. Results are also broadly similar in terms of factor exposures and conditional performance, where the properties during the live period are similar to those obtained in the historical backtest.

2. Comparison with Live Performance of Well-Known Competing Indexes

Section 1 provided ample evidence that performance over the live period of the Efficient MSR indexes has been attractive, and well-aligned with the longer historical backtest period. It is also interesting to compare the live performance to that of other smart beta indexes which rely on different concepts to generate outperformance. While there is now a plethora of smart beta indexes available, we focus here on the most popular indexes that also have long live periods. We notably consider the following competitors to the Efficient MSR indexes: the FTSE RAFI 1000 index, the MSCI Min Vol U.S. index, and the S&P 500 EW index. These three indexes, through both institutional mandates or ETPs, are those with the largest AUM in terms of replication. The RAFI 1000 index uses a composite fundamental metric of firm size both to select stocks and to attribute weights. The two other indexes reweight the constituents of the standard cap-weighted parent index, using a portfolio optimization with the objective to minimize volatility, respectively attributing simple equal weights. For comparison with the results of the Efficient MSR indexes, we provide results for the period from Nov. 23, 2009 to Dec. 31, 2014, as above. We focus on U.S. data, as data for other regions is not consistently available across the different competing indexes.

The performance statistics in the table below reveal that some smart beta indexes exhibited outperformance over cap-weighted indexes of almost negligible magnitude. Annual relative returns of both the RAFI index and the MSCI Min Vol index fall short of 1%. In this context, it is all the more remarkable that the efficient MSR indexes have achieved considerable outperformance over this period, which is well in line with their long-term backtest. The equal-weighted index for the U.S. achieved outperformance of more than 2.5% over the period, but this is slightly lower than the performance of the Efficient MSR indexes. However, since the tracking error of the latter is lower, the equal-weighted index does not reach the same level of relative risk-adjusted performance as that of the FTSE EDHEC-Risk Efficient index, which leads to an Information Ratio of 1.21 for the FTSE EDHEC-Risk Efficient index and only 0.9 for the equal-weighted index. It should also be noted that the MSCI Min Vol index clearly achieves the lowest volatility among all four indexes over this period, suggesting alignment with its volatility minimization objective.

Exhibit 6 provides an overview of conditional performance, depending on market regimes (bull and bear markets).

EXHIBIT 2

Performance Analysis – FTSE EDHEC-Risk Efficient U.S. Index and SciBeta U.S. Long-Term Efficient Maximum Sharpe Ratio Index

The table shows the return and risk performance of the FTSE EDHEC-Risk Efficient U.S. index and the SciBeta U.S. Long-Term Efficient Maximum Sharpe Ratio index. All statistics are annualized and daily total returns from Nov. 23, 2009 to Dec. 31, 2014 are used for the FTSE EDHEC-Risk Efficient U.S. index and from Dec. 31, 1974 to Dec. 31, 2014 for the SciBeta U.S. Long-Term Efficient Maximum Sharpe Ratio index. Returns are in USD. The "Secondary Market U.S. Treasury Bills (3M)" is the risk-free rate in US Dollars for U.S. The cap-weighted benchmark is the SciBeta U.S. CW index for the U.S. FTSE EDHEC-Risk Efficient index and for the U.S. LTTR Efficient MSR index, the benchmark is based on the 500 largest market cap U.S. stocks. Source: scientificbeta.com.

Performance Analysis	11/23/2009 to 12/31/2014 U.S. FTSE EDHEC-Risk Efficient	12/31/1974 to 12/31/2014 U.S. LTTR Efficient Maximum Sharpe Ratio
Annual Returns	18.43%	15.03%
Annual Volatility	16.01%	15.76%
Sharpe Ratio	1.15	0.63
Maximum Drawdown	19.11%	53.22%
Annual Relative Returns	3.21%	2.87%
Tracking Error	2.64%	4.33%
Information Ratio	1.21	0.66
95% Tracking Error	3.44%	7.26%
Maximum Relative Drawdown	4.22%	30.66%

EXHIBIT 3

Carhart Four-Factor Regression – FTSE EDHEC-Risk Efficient U.S. Index and SciBeta U.S. Long-Term Efficient Maximum Sharpe Ratio Index

The table shows the conditional performance and risk of the FTSE EDHEC-Risk Efficient U.S. index and the SciBeta U.S. Long-Term Efficient Maximum Sharpe Ratio index. All statistics are annualized. Analysis is based on daily total returns from Nov. 23, 2009 to Dec. 31, 2014 for the FTSE EDHEC-Risk Efficient index and from Dec. 31, 1974 to Dec. 31, 2014 for the U.S. LTTR. The Market factor is the daily return of the cap-weighted index of all stocks that constitute the index portfolio in excess of the risk-free rate. Small size factor is the daily return series of a cap-weighted portfolio that is long 30% smallest market cap stocks portfolios and short 30% largest market cap stocks of the universe. Value factor is the daily return series of a cap-weighted portfolio that is long 30% highest and short 30% lowest B/M ratio stocks of the universe. Momentum factor is the daily return series of a cap-weighted portfolio that is long 30% highest and short 30% lowest 52 weeks (minus most recent four weeks) past return stocks of the universe. The "Secondary Market U.S. Treasury Bills (3M)" is the risk-free rate in US Dollars for U.S.. The broad cap-weighted index of the corresponding region is used as the benchmark. Coefficients that are statistically significant at 95% confidence level are highlighted in bold. Source: scientificbeta.com.

Carhart Regression Analysis	11/23/2009 to 12/31/2014 U.S. FTSE EDHEC-Risk Efficient	12/31/1974 to 12/31/2014 U.S. LTTR Efficient Maximum Sharpe Ratio
Annual Alpha	3.04%	1.96%
Market Beta	0.95	0.91
SMB Beta	0.17	0.15
HML Beta	-0.02	0.11
MOM Beta	0.06	0.01
R-Squared	98.2%	95.9%

EXHIBIT 4

Conditional Performance Analysis – FTSE EDHEC-Risk Efficient U.S. Index and SciBeta U.S. Long-Term Efficient Maximum Sharpe Ratio Index

The table shows the conditional performance and risk of the FTSE EDHEC-Risk Efficient U.S. index and the SciBeta U.S. Long-Term Efficient Maximum Sharpe Ratio index. Calendar quarters with the corresponding region's positive cap-weighted benchmark returns comprise bull markets and the rest constitute bear markets. All statistics are annualized. Analysis is based on daily total returns from Nov. 23, 2009 to Dec. 31, 2014 for the FTSE EDHEC-Risk Efficient index and from Dec. 31, 1974 to Dec. 31, 2014 for the U.S. LTTR. The broad cap-weighted index of the corresponding region is used as the benchmark. Source: scientificbeta.com.

Conditional Performance Analysis	11/23/2009 to 12/31/2014 U.S. FTSE EDHEC-Risk Efficient	12/31/1974 to 12/31/2014 U.S. LTTR Efficient Maximum Sharpe Ratio
Bull Markets		
Annual Relative Returns	2.72%	2.10%
Tracking Error	2.47%	3.69%
Information Ratio	1.10	0.57
Bear Markets		
Annual Relative Returns	2.45%	3.78%
Tracking Error	3.20%	5.62%
Information Ratio	0.77	0.67

The most noteworthy finding is the clear defensive profile of the MSCI Min Vol strategy, as it delivered spectacular outperformance during bear periods but severe underperformance during the bull periods. The RAFI index, on the other hand, posted greater outperformance during bull periods. The FTSE EDHEC-Risk Efficient MSR index again showed balanced behavior over its live period, with similar outperformance in bull and bear periods. It is this balanced behavior that ultimately allows it to appear as the best performing index over a contrasted period with a succession of pronounced bull and bear markets.

3. Introducing Multi-Strategy Weighting

Scientific Beta offers many other diversification weighting schemes in addition to the Maximum Sharpe Ratio weighting scheme, each targeting a unique objective. Even though the different weighting schemes offer efficient diversification of stocks, there is an additional need for diversification of the weighting schemes to diversify away the strategy-specific risks — a concept called "Diversifying the Diversifiers.[8]" The combination of different strategies allows the diversification of risks that are specific to each strategy by exploiting the imperfect correlation between the different strategies. Thus, diversifying the model risks further reduces the unrewarded risks and renders the weighting scheme more robust. ERI Scientific Beta proposes a flagship offering of smart beta indexes based on this concept. The Diversified Multi-Strategy index combines, in equal proportions, the Efficient Maximum Sharpe Ratio, the Efficient Minimum Volatility, the Maximum Deconcentration, the Maximum Decorrelation and the Diversified Risk Weighted weighting schemes. These indexes, being better diversified, enable outperformance to be obtained over the long term compared to mono-strategy indexes.

Exhibit 7 presents the return/risk performance analysis of the different MSR indexes, the corresponding multi-strategy indexes and the Multi-Beta Multi-Strategy equal-weight indexes over the last 10 years. We can observe that the multi-strategy indexes either outperform the MSR strategies slightly in terms of risk/reward or provide a comparable performance in all regions. This improvement in performance can be further magnified if the multi-strategy scheme is combined with an explicit choice of factor exposure as in the Smart Beta 2.0 approach promoted by Scientific Beta, which is the case with the Multi-Beta Multi-Strategy Equal-Weight offering.

Thus, over the last 10-year period and for the same regions, we observe an average difference of 0.24%, with a maximum difference in the Developed Asia-Pacific ex-Japan region of 1.17%.

In the Developed World universe, we observe that the SciBeta Developed World Multi-Beta Multi-Strategy EW index outperforms the SciBeta Developed World Efficient MSR index by 0.25% annually.

Over longer periods, the differences are even more pronounced. Thus, for a period of 40 years, when referring to the long-term track records of the three methodologies applied to a universe of the top 500 U.S. capitalizations, we observe that the U.S. Multi-Beta Multi-Strategy EW LTTR outperforms the U.S. Efficient MSR LTTR by 1.08% annually. In the end, the U.S. Multi-Beta Multi-Strategy index with an Information Ratio of 0.79 and a Sharpe Ratio of 0.71 outperforms the U.S. Efficient MSR by 19.79% and 12.23%, respectively. •

EXHIBIT 5

Performance Analysis – FTSE EDHEC-Risk Efficient U.S. Index and its Competitors
The table shows the return and risk performance of the FTSE EDHEC-Risk Efficient U.S. index and its competitors: FTSE RAFI US 1000 index, MSCI Minimum Volatility index and S&P 500 Equal Weight index. All statistics are annualized and daily total returns from Nov. 23, 2009 to Dec. 31, 2014 are used. Returns are in USD. The "Secondary Market U,S, Treasury Bills (3M)" is the risk-free rate in US Dollars for U.S. The cap-weighted benchmark is the SciBeta U.S. CW index. FTSE® is a registered trade mark of the London Stock Exchange Plc and The Financial Times Limited. RAFI® is a registered trademark of Research Affiliates, LLC. MSCI® is a registered trademark of MSCI Inc. S&P® and S&P 500® are registered trademarks of Standard & Poor's Financial Services LLC ("S&P"), a subsidiary of The McGraw-Hill Companies, Inc. Source: scientificbeta.com.

U.S. 11/23/2009 to 12/31/2014	Broad CW	FTSE EDHEC-Risk Efficient	FTSE RAFI	MSCI Min Vol	S&P 500 EW
Annual Returns	15.22%	18.43%	16.20%	15.93%	17.79%
Annual Volatility	15.82%	16.01%	16.60%	11.92%	17.54%
Sharpe Ratio	0.96	1.15	0.97	1.33	1.01
Maximum Drawdown	18.58%	19.11%	21.08%	13.98%	22.71%
Annual Relative Returns	-	3.21%	0.97%	0.71%	2.56%
Tracking Error	-	2.64%	2.20%	5.46%	2.85%
Information Ratio	-	1.21	0.44	0.13	0.90
95% Tracking Error	-	3.44%	2.44%	7.74%	3.82%
Maximum Relative Drawdown	-	4.22%	4.92%	12.04%	6.94%

EXHIBIT 6

Conditional Performance Analysis – FTSE EDHEC-Risk Efficient U.S. Index and its Competitors
The table shows the conditional performance and risk of the FTSE EDHEC-Risk Efficient U.S. index and its competitors: FTSE RAFI US 1000 index, MSCI Minimum Volatility index and S&P 500 Equal Weight index. Calendar quarters with the corresponding region's positive cap-weighted benchmark returns comprise bull markets and the rest constitute bear markets. All statistics are annualized. Analysis is based on daily total returns from Nov. 23, 2009 to Dec. 31, 2014. The cap-weighted benchmark is the SciBeta U.S. CW index. FTSE® is a registered trademark of the London Stock Exchange Plc and The Financial Times Limited. RAFI® is a registered trademark of Research Affiliates LLC. MSCI® is a registered trademark of MSCI Inc. S&P® and S&P 500® are registered trademarks of Standard & Poor's Financial Services LLC ("S&P"), a subsidiary of The McGraw-Hill Companies, Inc.
Source: scientificbeta.com.

U.S. 11/23/2009 to 12/31/2014	FTSE EDHEC-Risk Efficient	FTSE RAFI	MSCI Min Vol	S&P 500 EW
Bull Markets				
Annual Relative Returns	2.72%	1.62%	-4.94%	3.44%
Tracking Error	2.47%	1.98%	4.96%	2.58%
Information Ratio	1.10	0.82	-1.00	1.33
Bear Markets				
Annual Relative Returns	2.45%	0.06%	14.85%	-1.23%
Tracking Error	3.20%	2.52%	7.17%	3.66%
Information Ratio	0.77	0.02	2.07	-0.34

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EXHIBIT 7

Performance Analysis – SciBeta Efficient Maximum Sharpe Ratio, Diversified Multi-Strategy, and Multi-Beta Multi-Strategy Indexes in Different Geographical Regions
This exhibit shows the return and risk performance of the SciBeta Efficient Maximum Sharpe Ratio, Diversified Multi-Strategy, and Multi-Beta Multi-Strategy Equal Weight indexes across different geographical regions: U.S., U.K., Eurozone, Japan and Developed Asia-Pacific ex-Japan. All statistics are annualized and daily total returns from Dec. 31, 2004 to Dec. 31, 2014 are used for the analysis. Returns are in USD/GBP/EUR/JPY/USD currencies for U.S./U.K./Eurozone/Japan/Developed Asia-Pacific ex-Japan, respectively. The "Secondary Market U.S. Treasury Bills (3M)" is the risk-free rate in US Dollars for U.S. and Developed Asia-Pacific ex-Japan. The "U.K. Treasury Bill Tender (3M)" is the risk-free rate in British Pounds for U.K. "Euribor (3M)" is the risk-free rate in Euros for Eurozone, and "Japan Gensaki T-Bill (1M)" is the risk-free rate in Japanese Yen for Japan. The cap-weighted benchmark is the SciBeta CW index of the corresponding universe. Source: scientificbeta.com.

Analysis Period 12/31/2004 to 12/31/2014 (10 Years)	U.S.			U.K.			Eurozone			Japan			Developed ex-Japan Asia-Pacific		
	Efficient MSR	Diversified Multi-Strategy	MBMS EW	Efficient MSR	Diversified Multi-Strategy	MBMS EW	Efficient MSR	Diversified Multi-Strategy	MBMS EW	Efficient MSR	Diversified Multi-Strategy	MBMS EW	Efficient MSR	Diversified Multi-Strategy	MBMS EW
Annual Returns	9.57%	9.57%	9.88%	10.79%	10.19%	10.02%	7.14%	6.87%	7.43%	5.97%	5.81%	6.17%	11.28%	11.13%	12.46%
Annual Volatility	19.43%	19.81%	19.30%	17.89%	17.91%	17.45%	17.43%	17.92%	17.31%	19.50%	20.01%	19.17%	20.42%	20.83%	20.07%
Sharpe Ratio	0.42	0.41	0.44	0.48	0.45	0.45	0.30	0.28	0.32	0.30	0.28	0.31	0.48	0.47	0.55
Maximum Drawdown	52.35%	52.73%	51.93%	41.26%	44.71%	45.47%	57.07%	57.70%	57.09%	51.39%	52.84%	49.26%	65.11%	64.85%	63.28%
Annual Relative Returns	1.67%	1.67%	1.97%	3.49%	2.89%	2.71%	1.72%	1.46%	2.01%	1.99%	1.83%	2.19%	1.62%	1.46%	2.79%
Tracking Error	2.82%	2.50%	3.17%	4.81%	4.68%	5.50%	5.47%	4.79%	5.56%	5.76%	5.23%	6.97%	6.29%	5.45%	6.23%
Information Ratio	0.59	0.67	0.62	0.73	0.62	0.49	0.32	0.30	0.36	0.35	0.35	0.31	0.26	0.27	0.45
95% Tracking Error	5.10%	4.53%	5.65%	8.97%	8.80%	10.16%	10.06%	8.75%	10.47%	11.62%	10.04%	13.83%	12.25%	10.59%	12.57%
Max Relative Drawdown	5.57%	5.77%	5.39%	10.02%	14.09%	17.66%	9.21%	8.81%	10.45%	10.10%	10.44%	12.24%	10.91%	9.12%	11.05%

EXHIBIT 8

Performance Analysis – SciBeta Efficient Maximum Sharpe Ratio, Diversified Multi-Strategy, and Multi-Beta Multi-Strategy Indexes in the Developed World
This exhibit shows the return and risk performance of the SciBeta Efficient Maximum Sharpe Ratio, Diversified Multi-Strategy and Multi-Beta Multi-Strategy Equal Weight indexes in the Developed World universe. All statistics are annualized and daily total returns from Dec. 31, 2004 to Dec. 31, 2014 are used for the analysis. Returns are in USD. The "Secondary Market U.S. Treasury Bills (3M)" is the risk-free rate. The cap-weighted benchmark is the SciBeta Developed World CW index. Source: scientificbeta.com.

Analysis Period 12/31/2004 to 12/31/2014 (10 Years)	Developed World			
	Broad CW	Efficient MSR	Diversified Multi-Strategy	Multi-Beta Multi-Strategy EW
Annual Returns	6.73%	8.54%	8.42%	8.79%
Annual Volatility	17.04%	15.70%	16.04%	15.63%
Sharpe Ratio	0.31	0.45	0.44	0.47
Maximum Drawdown	57.13%	53.96%	54.79%	53.94%
Annual Relative Returns	-	1.81%	1.69%	2.06%
Tracking Error	-	2.33%	2.00%	2.59%
Information Ratio	-	0.78	0.85	0.80
95% Tracking Error	-	4.62%	3.90%	5.07%
Maximum Relative Drawdown	-	4.04%	4.07%	6.37%

EXHIBIT 9

Performance Analysis – SciBeta Efficient Maximum Sharpe Ratio, Diversified Multi-Strategy and Multi-Beta Multi-Strategy Indexes with U.S. Long-Term Track Records
This exhibit shows the return and risk performance of the SciBeta Efficient Maximum Sharpe Ratio, Diversified Multi-Strategy and Multi-Beta Multi-Strategy Equal Weight indexes with U.S. Long-Term Track Records. All statistics are annualized and daily total returns from Dec. 31, 1974 to Dec. 31, 2014 are used for the analysis. Returns are in USD. The "Secondary Market U.S. Treasury Bills (3M)" is the risk-free rate. The cap-weighted benchmark is based on the 500 largest market cap U.S. stocks. Source: scientificbeta.com.

Analysis Period 12/31/1974 to 12/31/2014 (40 Years)	U.S. LTTR			
	Broad CW	Efficient MSR	Diversified Multi-Strategy	Multi-Beta Multi-Strategy EW
Annual Returns	12.16%	15.03%	14.79%	16.11%
Annual Volatility	17.12%	15.76%	16.05%	15.58%
Sharpe Ratio	0.41	0.63	0.60	0.71
Maximum Drawdown	54.53%	53.22%	54.55%	53.86%
Annual Relative Returns	-	2.87%	2.64%	3.95%
Tracking Error	-	4.33%	4.07%	4.98%
Information Ratio	-	0.66	0.65	0.79
95% Tracking Error	-	7.26%	7.67%	8.95%
Maximum Relative Drawdown	-	30.66%	32.89%	33.65%

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Looking at Value through a New Lens

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The value factor is one of the most consensual and most widely-documented factors. There is ample evidence and numerous theoretical explanations suggesting that tilting an equity portfolio toward low valuation stocks allows above-market returns to be harvested. Traditionally, the value factor was seen as one factor among others that existed, while being distant from the latter factors. This is the case most notably in the Fama and French three-factor model or the Carhart four-factor model, where the value factor coexists with the size and momentum factors. While size and momentum are not uncorrelated with value, they do not create a dramatic overlap or question the role of value as a factor on its own right. Quite to the contrary, it has been shown that the momentum factor takes on the role of a diversifier of value-tilted portfolios with both factor tilts suitably complementing each other (see Asness, Moskowitz and Pedersen 2013).

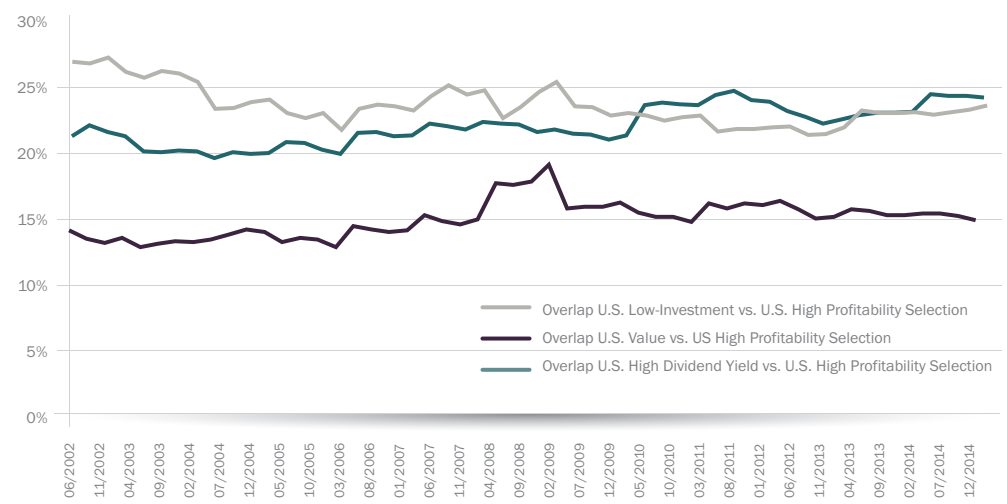
However, recent research in empirical finance has come up with new multi-factor models, augmenting the abovementioned models with additional factors based notably on firms' investment decisions. These new factors are the low-investment factor and the high-profitability factor. More recently, authors have documented profitability and investment as factors that explain a cross-section of stock returns and presented robust evidence that there is a premium associated with these factors. The empirically observed effects of investment and profitability have led other researchers to integrate these factors in multi-factor models of asset returns. Fama and French (2014) recently introduced a five-factor model which adds investment and profitability factors to their well-known three-factor model (containing the market, value and size factors). They find that this augmented model improves explanatory power for the cross-sectional variation in expected returns. Similarly, Hou, Xue, and Zhang (2014) tested a four-factor model containing the market, size, profitability and investment factors and find that it is successful in explaining cross-sectional return patterns and profits for many well-known profitable equity trading strategies.

Given the emergence of these new factor models, discussion among researchers and practitioners has recently turned to the link between the well-known value factor on the one hand, and the profitability and investment factors on the other. This article aims to examine this link. In particular, a common question investors may have in practice is if value is not redundant with the profitability or investment factors.

We should first note that using a value tilt does not mean taking a view on the best proxy for a true factor model of asset pricing. Factor-tilted indexes for various factors allow investors to tilt toward — or, instead, away from — a large number of commonly employed factors. Of those factor tilts, some can be expected to be rewarded in the long term, based on empirical evidence and economic rationale. Among these rewarded tilts, one can notably list the low-size tilt, value tilt, high-momentum tilt, low-volatility tilt, low-investment tilt and profitability tilt. Of course, these tilts are not entirely uncorrelated, and the empirical literature documenting the long-term premia on these factors has never argued that they are entirely uncorrelated. For investors who wish to harvest a premium associated with these factor tilts, the fact that they may be — to some extent — correlated does not in any way influence the expected return benefit from taking on such tilts. However, from a diversification perspective, having tilts that are highly correlated will lower the benefit of using a multi-factor combination as opposed to a single-factor tilt. Conversely, having factor tilts with very low correlation will increase the diversification benefits of using multiple factors rather than a single factor. Therefore, from a diversification perspective it is interesting to ask whether factors are — to some degree — correlated or overlapping.

EXHIBIT 1

Percentage overlap of constituents in high profitability with low investment, value, and high dividend yield (time series of the percentage overlap at each rebalancing date)



Interestingly, for value and profitability, it has been widely documented that correlation is remarkably low. In that sense, profitability is often prescribed as a factor that combines well with a value factor tilt. See in particular Novy-Marx (2013), who writes, "Because strategies based on profitability are growth strategies, they provide an excellent hedge for value strategies, and thus dramatically improve a value investor's investment opportunity set. In fact, the profitability strategy, despite generating significant returns on its own, actually provides insurance for value; adding profitability on top of a value strategy reduces the strategy's overall volatility." The empirical evidence therefore suggests that high-profitability factor indexes can be suitably combined with value factor indexes to form multi-factor allocations with considerable diversification benefits.

We provide the following illustrations concerning overlap across different factor tilts. First, we look at the differences in composition between stock selections of the highest profitability vs. value stocks (as defined by high book-to-market) and high-dividend-yield stocks. Second, we look at differences in the fundamental metrics of these different stock selections.

In Exhibit 1 above, we display the time series of the percentage of overlap (as defined by the number of stocks that belong to both selections divided by the total number of stocks that belong to one of the two selections) between the High Profitability selection and respectively the Low Investment, Value and High Dividend selections, in the Scientific Beta U.S. Universe, between June 21, 2002 (index inception dates) and Dec. 19, 2014 rebalancing dates.

The lowest overlap overall is between the Value and High Profitability selections, at around 14% on average over the period. The highest overlap is between Low Investment and High Profitability, but it still lies at a reasonable level, with an average of 23% over the period.

In Exhibit 2, we summarize the average fundamental characteristics (Price-to-Earnings (including and excluding negative earnings), Price-to-Book, Price-to-Cash Flow, Price-to-Sales and Dividend Yield) of maximum deconcentration indexes that are based on equally weighting the stocks selected according to, respectively, High Profitability, Low Investment, Value and High Dividend. Data is as of the December 2014 rebalancing date. We compare them to their SciBeta cap-weighted reference index. Those fundamental ratios are, for some investors, an indication of comparative average valuation level of indexes against a reference.

We observe that the High-Profitability-selection-based index exhibits the highest valuation ratios and the lowest dividend yield, compared to other selection-based indexes as well as against the cap-weighted reference index. For example, the High Profitability Index exhibits a Price-to-Book of 4.6 while other indexes exhibit a value of less than 3. This is an indication that the High Profitability selection overlaps poorly with the Value selection. Also, the High Profitability selection exhibits the lowest dividend yield against other indexes. We also observe that the Low-Investment-selection-based indexes exhibit the lowest weighted average dividend yield, against other types of selection.

Overall, these two exhibits clearly illustrate that value-oriented stock selections differ considerably from high-profitability selections, thus providing ample diversification potential between value and high-profitability tilts. Moreover, value selections do not appear redundant with low-investment selections despite some commonality.

What is more, it should be noted that Fama and French (2014), when they develop an extended version with five factors of their three-factor model, include the market, size, value, profitability and investment factors in this new factor model, arguing that it is useful to include all five factors. In line with this research, some investors are using all of these five factors together. However, a widely quoted result in the Fama and French (2014) paper is that value is a "redundant factor" in the presence of the other four factors. What this means is that value does not carry any premium which could not be explained by its own exposure to the four other factors. From an investment perspective, this result only confirms

that the premium for value should reasonably exist, given that it can be explained by exposure to well-documented rewarded factors. However, redundancy of the value factor would mean that there is not any additional diversification benefit from including value alongside the other four factors. It should be noted that the result derived by Fama and French hinges on two specific characteristics of the setup they use. First, they exclude the momentum factor from their analysis. Asness (2014) and Asness, Frazzini, Israel and Moskowitz (2015) provide evidence that, if momentum is included in addition to the five factors in the Fama and French (2014) five-factor model, then value is not a redundant factor. This suggests that for an investor who tilts toward momentum, low investment, high profitability and momentum, adding a value tilt will have favorable diversification effects. Second, Asness, Frazzini, Israel and Moskowitz (2015) show that value is only redundant in the five-factor model excluding momentum when using a definition of value which is quite far removed from practical value implementations. In particular, when scoring stocks by a book-to-market ratio that uses the current price and the lagged book value, which corresponds to the approach used in practice by most providers of value indexes, the value factor is not redundant relative to the other four factors. However, Fama and French (2014) use a value factor which is based on scoring stocks by a book-to-market ratio, which uses the lagged price coinciding with the end of the fiscal year for which book value is reported, and this same book value. While this approach can be justified from the perspective of matching the date of book value and price, in practical value investing, it arguably does not make much sense to ignore the current price when scoring stocks by valuation metrics. In the end — as Asness, Frazzini, Israel and Moskowitz (2015) write— "the value factor, rendered … redundant by the Five Factor Model, is …easily resurrected."

Their key result appears clearly in the table below, extracted from their paper, which is based on U.S. data from 1963 to 2013. In the table below, RMRF denotes the market factor, SMB the size factor, RMW the profitability factor, CMA the low investment factor, UMD the momentum factor, HML the standard Fama and French value factor, and HML-DEV the more timely value factor. It appears clearly from the results that, in the presence of momentum, the timely HML-DEV factor generates excess returns that are not captured by the other five factors. The unexplained annualized return (Intercept) is 4.87% with a t-stat in excess of four.

Overall, the finding of value's redundancy is not particularly relevant for the practical benefits of using a value tilt. In fact, whether or not value is redundant, there is robust evidence that value investing leads to a long-term premium. Moreover, the finding of redundancy is not robust when including a momentum factor or using a more practical definition of value. Therefore, in a practical context, value is not even likely to be redundant.

Of course, a discussion of suitable combinations is useful. However, investors may consider taking an agnostic approach on this and consider factor indexes for a range of factors, which can be used as suitable building blocks in allocations across various factors. In this sense, the low-investment and high-profitability factors are suitable additions to the investor's menu of factor tilts. These two factors are thoroughly documented as rewarded factors, both in terms of empirical evidence and economic rationale. Moreover, these factors are neither subsumed by other factors such as value and momentum, nor do they make these other factors redundant. Investors can thus choose to combine low-investment and high-profitability-tilted indexes with other rewarded factor tilts (such as momentum, value, low size and low volatility) depending on their investment objectives, their constraints and their investment beliefs. •

EXHIBIT 2

Fundamental metrics of stock selections for U.S. SciBeta Indexes

Fundamental Attribute	SciBeta U.S. High Profitability Max Deconcentration Index	SciBeta U.S. Low Investment Max Deconcentration Index	SciBeta U.S. Value Max Deconcentration Index	SciBeta U.S. High Dividend Max Deconcentration Index	SciBeta U.S. Cap-Weighted Reference Index
Price/Earnings	22.48	19.01	18.53	19.64	19.5
Price/Earnings (ex-negative earnings)	21.6	18.3	17.68	18.87	18.91
Price/Cash Flow	13.91	10.65	9.3	10.16	11.29
Price/Sales	1.85	1.4	1.26	1.51	1.82
Price/Book Value	4.6	2.61	1.88	2.59	2.95
Dividend Yield	1.45%	1.97%	2.02%	2.78%	1.92%

EXHIBIT 3

The Value Factor in Alternative Multi-Factor Models

	Intercept	RMRF	SMB	RMW	CMA	UMD	R-Squared
HML	-0.48% (-0.46)	0.01 (0.37)	0.02 (0.81)	0.23 (5.36)	1.04 (23.03)		52%
HML	0.52% (0.51)	-0.01 (0.35)	0.03 (1.04)	0.24 (5.95)	-1.03 (23.37)	-0.11 (-0.46)	54%
HML-DEV	0.23% (0.15)	0.06 (2.04)	0.00 (0.11)	-0.02 (-0.30)	0.95 (14.24)		28%
HML-DEV	4.87% (4.74)	-0.01 (-0.32)	0.03 (1.15)	0.07 (1.60)	0.89 (20.01)	-0.53 (-27.31)	68%

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Does Smart Beta Work Well Only in Backtests? A Discussion of Robustness Issues

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There has been significant evidence that systematic equity investment strategies (so-called smart beta strategies) outperform cap-weighted benchmarks over the long run. These strategies are usually marketed on the basis of outperformance. However, it is important to recognize that performance analysis is typically conducted on backtests that apply the smart beta methodology to historical stock returns. Concerning actual investment decisions, a relevant question therefore is how robust the outperformance is.

In general, robustness refers to the capacity of a system to perform effectively in a constantly changing environment. In the context of smart beta strategies, two kinds of robustness need to be taken into account — relative robustness and absolute robustness. A strategy is assumed to be "relatively robust" if it is able to deliver similar outperformance in similar market conditions. Single-factor indexes aim to achieve this kind of robustness. Absolute robustness is the capacity of the strategy to deliver risk-adjusted performance in the future to a degree that is comparable to that of the past owing to a well-understood economic mechanism rather than just by chance. Absolute robustness, in other words, is the absence of pronounced state and/or time dependencies and a strategy shown to outperform irrespective of prevailing market conditions can be termed robust in absolute terms.

Potential causes of lack of robustness

Lack of robustness in smart beta strategies can be caused mainly by exposure to four different risks in the strategy construction process — factor fishing and model mining, specific risks, and strong factor dependencies. While the first two issues can have a major influence on relative robustness, the last point is at the heart of the issue of absolute robustness.

Factor fishing and model mining risks as causes for lack of relative robustness

Investors who wish to benefit from factor premia need to address robustness when selecting a set of factors. Harvey et al. (2013) document a total of 314 factors with a positive historical risk premium, showing that the discovery of the premium could be a result of data mining, i.e. strong and statistically significant factor premia may be a result of many researchers searching through the same dataset to find publishable results. For example, when capturing the value premium one may use extensive fundamental data including not only valuation ratios but also information on, for example, the sales growth of the firm.

While there is an economic rationale for the value factor that is compatible with asset pricing theory, selection of stocks by fundamental data returns to the argument of mispriced or undervalued stocks, which is not based on any theoretical corpus. We perceive that this argument of mispricing for growth tech stocks favors the design of a fundamentals-based strategy after the tech bubble. This kind of weighting scheme consequently gives a sector bias to the strategy and is otherwise not based on any fundamental criterion that is associated with a long-term risk premium.

Therefore, a key requirement for investors to accept factors as relevant in their investment process is that there is a clear economic intuition as to why the exposure to this factor constitutes a systematic risk (Kogan and Tian, 2013). Failure to recognize a suitable proxy for the rewarded factor will harm the relative robustness of the strategy.

Model mining risk is the risk of having an index construction methodology that results in a good track record in backtesting. Many value-tilted indexes include a large set of ad-hoc methodological choices, opening the door to data mining.

Exposures to specific risks as cause for lack of relative robustness

All smart beta strategies are exposed to unrewarded strategy-specific risks. Specific risks correspond to all the risks that are unrewarded in the long run, and therefore not ultimately desired by the investor. In line with portfolio theory, among the unrewarded risks we find specific financial risks (also called idiosyncratic stock risks), which correspond to the risks that are specific to the company itself. It is this type of risk that asset managers are supposed to be the best at knowing, evaluating and choosing in order to create alpha, but portfolio theory considers it to be neither predictable nor rewarded, so it is better to avoid it by investing in a well-diversified portfolio.

Specific risks can also correspond to important financial risk factors that do not explain, over the long term, the value of the risk premium associated with the index. The academic literature considers, for example, that commodity, currency and sector risks do not have a positive long-term premium. For example, value strategies often lead to pronounced tilts toward financial sector stocks. During the financial crisis of 2008, exposure to the financial sector proved to be a major determinant of performance of these strategies. It should be noted that the tilt toward the financial sector may not be desired, but it came as a by-product of holding value stocks.

Model-specific risks that are specific to the implementation of the diversification model are also a form of unrewarded risk. As per Modern Portfolio Theory, every investor should optimally combine risky assets so as to achieve the highest possible Sharpe ratio. 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 the benefits of optimal portfolio diversification.

Dependency on individual factor exposures as cause for lack of absolute robustness

Systematic risks come from the fact that smart beta strategies can be more or less exposed to particular risk factors depending on the methodological choices guiding their construction (implicit) but also on the universe of stocks supporting this construction scheme (explicit). For example, fundamentals-weighted portfolios typically have a value tilt, and minimum-volatility strategies exhibit a low-beta tilt (see, for example, Scherer, 2011, Blitz and Swinkels, 2008, and Amenc, Goltz and Le Sourd, 2008). Each weighting scheme exposes investors to implicit risk factors which may or may not be consistent with their risk objective. It is important to note that periods of poor performance in all factors are common throughout long-horizon historical tests and the underperformance occurs at different points in time. Therefore, investing in a single factor is not a robust approach in absolute terms, as the performance will vary greatly over time across different time periods.

Improving robustness

We propose three ways in which the robustness of various smart beta strategies can be improved.

Avoidance of data or model mining through a consistent framework

A very effective mechanism to avoid data mining is by establishing a consistent framework for smart beta index creation, thus limiting the choices while providing the flexibility needed for smart beta index creation. Consistency in the index framework has two main benefits. First, it prevents model mining by limiting the number of choices through which indexes can be constructed. A uniform framework is the best safeguard against post hoc index design, or model mining (i.e., the possibility of testing a large number of smart beta strategies and publishing the ones that have good results).

Second, analysis across specification choices is vital because the range of outcomes gives a more informative view than a single specification, which could always have been picked. An index that performs well across multiple specification choices is more robust than an index that performs only in a single specification choice which could very well have been by chance rather than because of the robustness of the strategy. Pre-packaged indexes do not allow investors to compare across specifications in order to obtain a view on the sensitivity of performance to index specification choices, thereby exposing investors to a risk of unintended consequences of undesired risks.

Another approach to the inconsistency of the conceptual framework is to look at the evolution or change of methodology over time for the same strategy or the same factor. Some index providers have launched new factor indexes when they already had factor indexes for the same factor on the market. In this case, the new indexes have the same objective as the old ones but different construction principles. This phenomenon has a striking resemblance to the practice of funds or asset managers of creating new funds or changing the strategy of funds in order to overshadow the poor track record of the old fund. Thus, an inconsistent framework over time is also a kind of model mining that allows the index providers to launch new indexes with better track records.

Improving relative robustness by reducing unrewarded risks

Relative robustness can be improved by minimizing the unrewarded risk as much as possible. There are numerous approaches to estimating risk parameters. The sample estimator of a covariance matrix produces extremely high estimation errors when the ratio of universe size to sample size is large (Kan and Zhou, 2007) — sample risk. One solution to this problem is to reduce the number of parameters to be estimated by imposing a structure on the covariance matrix (Chan et al., 1999). Although this method reduces sample risk, its drawback is that the estimator is biased if the risk model does not conform to the true stock-return-generating process — model risk. The next generation of estimators aims to achieve a tradeoff between sample risk and model risk by combining sample estimators and structured estimators (Ledoit and Wolf, 2003). Another way to reduce model risk, and not necessarily at the cost of sample risk, is to use an implicit factor model such as principal component analysis (PCA), especially when implementing PCA while limiting the number of statistical factors using Random Matrix Theory in order to achieve parsimony and robustness (Plerous et al., 2002).

One serious concern with optimization-based weighting schemes is that the stocks with the highest estimation error may receive the highest weight — a process commonly

known as "Error Maximization" — which is detrimental to the relative robustness of the strategies. In practice, various kinds of deconcentration constraints are adopted to improve diversification. Jagannathan and Ma (2003) provided empirical evidence that imposing non-negativity constraints removes large outliers and hence provides better performance through better diversification. Deconcentration constraints ensure sufficiently balanced weights across constituents. DeMiguel et al. (2009) introduce flexible quadratic constraints that put limits on the overall amount of concentration in the portfolio (e.g., on the sum of squares of portfolio weights) rather than limiting the weight of each stock in the portfolio, thus leaving more room for the optimizer while avoiding concentration overall.

Even though different weighting schemes offer efficient diversification of stocks, there is a need for additional diversification of the weighting schemes to diversify away the strategy-specific risks — a concept called "Diversifying the Diversifiers."[9] The combination of different strategies diversifies risks that are specific to each strategy by exploiting the imperfect correlation between the different strategies' parameter estimation errors. Thus, diversifying the model risks further reduces the unrewarded risks and renders the weighting scheme more robust (in a relative manner).

Improving absolute robustness by diversifying across factors

As discussed before, investors who rely on single factor exposure take the risk of the likelihood of the underlying factor underperforming over short periods. The reward for exposure to these factors has been shown to vary over time (see e.g., Harvey, 1989, Asness, 1992, Cohen, Polk and Vuolteenaho, 2003). If this time variation in returns is not completely in sync for different factors, allocating across factors allows investors to diversify the sources of their outperformance and smooth their performance across market conditions.

Overview: how to improve robustness in smart beta performance

To conclude the section on improvement of robustness, Exhibit 1 summarizes how to improve robustness in smart beta performance.

Assessing conditional performance, outperformance probability, and live performance

When assessing the robustness of a smart beta strategy, one necessarily needs to rely on a conceptual analysis of the strategy design. Purely evaluating performance data will not be conclusive on the question of the degree of robustness of a strategy. For example, a strategy that has been derived from extensive data mining may well be performing well in a long-term historical data set, if the time period and data set essentially correspond to those that had been used to design an over-fitted strategy. Even when assessing out-of-sample performance, one might not be able to detect a lack of robustness if the out-of-sample period is relatively short. In fact, over any short time period, a given strategy could generate performance benefits purely due to chance. At the end of the day, what would be needed for a conclusive assessment is long-term live performance, ideally spanning several decades, which simply is not available for any of the commercially available smart beta indexes. This does not mean, however, that we should not look at performance data to inform our evaluation of robustness. In fact, there are essentially two ways in which we can assess robustness by deviating voluntarily from the backtest time frame which may have been used to data-mine a strategy prior to launch. First, we can exploit any reasonably long historical backtrack, and divide it into sub-samples reflecting certain market or factor conditions. Such an assessment specifically uncovers some of the sensitivities of performance to market factors that may be hidden in a longer-term backtest average performance result. Second, we can assess robustness by looking at the historical probability of outperforming the cap-weighted reference index over a given investment horizon. This is an intuitive measure to show how often the strategy has managed to outperform the cap-weighted reference index in the past. It is calculated by computing the probability of obtaining positive excess returns if one invests in the strategy for a given time period (e.g., three years) at any point during the complete history of the strategy. Third, we can of course assess live performance, even if it is relatively short, to get an idea of a strategy's behavior in a real investment context on a post-launch basis.

EXHIBIT 1

Best practices to improve robustness

Category	Best Practices: Requirements for Robustness	Common Practice: Risk of a Lack of Robustness
Methodology	Consistent framework	Ad-hoc methodologies open the door for data mining/model mining
Factor definitions	Simple, tried and tested factors (e.g. Book-to-Price for 'Value')	Complex, proprietary and unproven factor definitions (e.g. use of proprietary variables, adjustments or constraints)
Weighting scheme	Diversification of model risk and robust risk parameter estimation	Choice of a single weighting model and high sensitivity to input parameters
Transparency	Full transparency — free access to historical constituents and weights and unambiguous ground rules	Opaque and restricted or no access to back test data with ambiguous ground rules

EXHIBIT 2

Conditional performance (over the broad CW benchmark) of the FTSE RAFI 1000 Developed Index, MSCI World Equal Weighted Index, MSCI World Minimum Volatility Index, FTSE Developed Diversified Factor Index, MSCI World Quality Mix Index, Scientific Beta Multi-Beta Multi-Strategy (EW) and Scientific Beta Multi-Beta Multi-Strategy (ERC). The analysis is based on daily total return data in USD from 12/31/2004 to 12/31/2014 (10 years). All statistics are annualized. The benchmark is the cap-weighted portfolio of all stocks in the investible universe. Data source: Bloomberg and www.scientificbeta.com.
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Developed World 12/31/2004 - 12/31/2014	SciBeta Developed MBMS EW	SciBeta Developed MBMS ERC	FTSE RAFI Developed	MSCI World Equal Weighted	MSCI World Minimum Volatility
Bull Markets					
Annual Relative Returns	0.76%	0.99%	2.77%	2.45%	-6.65%
Annual Tracking Error	2.11%	1.82%	3.96%	3.07%	7.31%
Information Ratio	0.36	0.54	0.70	0.80	-0.91
Bear Markets					
Annual Relative Returns	3.24%	2.68%	-3.15%	-2.26%	11.72%
Annual Tracking Error	3.53%	3.31%	5.03%	4.89%	9.17%
Information Ratio	0.92	0.81	-0.63	-0.46	1.28

Conditional performance

The exhibit above provides a conditional performance assessment using 10 years of data.

It is clear that the multi-strategy multi-factor indexes are much more robust to factor conditions. They tend to deliver outperformance without much dependence on individual factor returns.

The picture is different for Smart Beta 1.0 strategies, which provide implicit exposure to only one or perhaps two factors, thus leading to high sensitivity of performance to factor regimes for individual factors.

Probability of outperformance

Since the performance of smart beta varies over time, the analytics reported over long horizons, for example excess returns over 10 years, have limited information because of averaging over time periods. Probability of outperformance is a measure that overcomes this limitation. The probability of outperformance is defined as the empirical frequency of outperforming the cap-weighted reference index over a given investment horizon. It is an intuitive and relevant measure that shows how often and consistently the strategy would be able to outperform the cap-weighted reference index in the past for all possible entry points. It comes in handy to differentiate between two strategies that have similar long-term performance, although one has small but consistent outperformance while the other benefits from a few periods of high gains combined with long runs of losses. In this example, the former strategy is more robust in an absolute sense and the performance of the latter is disrupted and accompanied by risk.

Exhibit 4 below presents the one-year, three-year and five-year probabilities of outperformance of the FTSE RAFI 1000 Developed Index, MSCI World Equal Weighted Index, MSCI World Minimum Volatility Index, FTSE Developed Diversified Factor Index, MSCI World Quality Mix Index, Scientific Beta Multi-Beta Multi-Strategy (EW) and Scientific Beta Multi-Beta Multi-Strategy (ERC) for the past 10 years. We can clearly see that the SciBeta MBMS EW and ERC strategies have higher outperformance probabilities than single-factor strategies and are thus more robust in delivering consistent outperformance.

As a conclusion, what about live performance?

Many investors consider that smart beta is often sold as a substitute for an active manager, so it seems relevant to look at the indexes' live track records, too. While it appears difficult to find long-duration live track records for the new generations of smart factors and multi-factors or multi-smart-factor indexes, it is possible to appraise the robustness of the first generations of smart beta indexes. Below, we present the live performances of four popular smart beta strategies, namely FTSE EDHEC-Risk Efficient U.S., FTSE RAFI U.S., S&P EW and MSCI Minimum Volatility US.

The considerable difference in live performance is, in our view, testimony to the attention paid by the designer of the methodology to offering robust weighting schemes over and above the simulated performance. •

[9] *See Timmermann (2006), Kan and Zhou (2007), Tu and Zhou (2011) and Amenc, Goltz, Lodh, Martellini (2012) on the benefits of combining portfolio strategies.*

LIVE IS BETTER

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

With live annualised outperformance of 2.37%,[1] these Smart Beta 1.0 indices based on the Efficient Maximum Sharpe Ratio methodology have shown that a good diversification method can lead to significant and robust outperformance over cap-weighted indices.

Since 2013, with the Smart Beta 2.0 framework, EDHEC-Risk Institute has created Scientific Beta multi-smart-factor indices that are even better diversified and therefore more successful. Over the long term, these indices exhibit outperformance of 3.85%[2] compared to their cap-weighted benchmark and have outperformed our Smart Beta 1.0 offering over the live period.[3]

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

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

www.scientificbeta.com

1 - The average annualised returns of the FTSE EDHEC-Risk Efficient Developed Index are 13.00%, compared to 10.63% for its cap-weighted benchmark, computed using daily total returns from November 23, 2009 (live date) to December 31, 2014.
2 - The average annualised returns observed with US data over 40 years (December 31, 1974 to December 31, 2014) of the Scientific Beta US Multi-Beta Multi-Strategy EW index are 16.11% and 15.91% respectively, compared to 12.16% for a reference index based on the 500 largest market-cap US stocks.
3 - The average live outperformance across all Scientific Beta developed regions of Scientific Beta Multi-Beta Multi-Strategy (Equal Weight and Equal Risk Contribution) indices is 3.47% and 3.39% respectively, while that of the Efficient Maximum Sharpe Ratio strategy in the same period is 2.53%. This live analysis is based on daily total returns in the period December 20, 2013 (live date) to December 31, 2014 for following developed world regions – USA, Eurozone, UK, Developed Europe ex UK, Japan, Developed Asia Pacific ex Japan, Developed ex UK, Developed ex USA, Developed, and Extended Developed Europe. The benchmark used is a cap-weighted portfolio of all stocks in the respective Scientific Beta universes.

EXHIBIT 3

Conditional excess returns (over the broad CW benchmark) of the FTSE RAFI 1000 Developed Index, MSCI World Equal Weighted Index, MSCI World Minimum Volatility Index, FTSE Developed Diversified Factor Index, MSCI World Quality Mix Index, Scientific Beta Multi-Beta Multi-Strategy (EW) and Scientific Beta Multi-Beta Multi-Strategy (ERC). The quarters are divided into top and bottom 25 percentiles based on returns of the Market, HML, SMB and Low Volatility factors. The SMB factor is the daily return series of a cap-weighted portfolio that is long small-cap stocks and short the 30% largest market-cap stocks in the investible universe. The HML factor is the daily return series of a cap-weighted portfolio that is long the 30% highest and short the 30% lowest B/M ratio stocks in the investible universe. The Low Volatility factor is the daily return series of a cap-weighted portfolio that is long the 30% lowest and short the 30% highest 104-week returns volatility stocks in the investible universe. The analysis is based on daily total return data in USD from 12/31/2004 to 12/31/2014 (10 years). All statistics are annualized. The benchmark is the cap-weighted portfolio of all stocks in the investible universe. Data source: Bloomberg and www.scientificbeta.com.
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Annual Excess Returns (over CW)	Top 25% Quarters by Market factor returns	Bottom 25% Quarters by Market factor returns
SciBeta Dev Multi-Beta Multi-Strategy (EW)	-1.49%	3.29%
SciBeta Dev Multi-Beta Multi-Strategy (ERC)	-0.56%	2.70%
FTSE RAFI Developed 1000 Index	10.78%	-3.86%
MSCI World Equal Weighted Index	8.70%	-2.08%
MSCI World Minimum Volatility Index	-14.46%	12.34%
Annual Excess Returns (over CW)	**Top 25% Quarters by SMB factor returns**	**Bottom 25% Quarters by SMB factor returns**
SciBeta Dev Multi-Beta Multi-Strategy (EW)	2.97%	-0.06%
SciBeta Dev Multi-Beta Multi-Strategy (ERC)	3.34%	-0.56%
FTSE RAFI Developed 1000 Index	5.77%	-3.30%
MSCI World Equal Weighted Index	9.55%	-5.02%
MSCI World Minimum Volatility Index	-7.30%	6.92%
Annual Excess Returns (over CW)	**Top 25% Quarters by HML factor returns**	**Bottom 25% Quarters by HML factor returns**
SciBeta Dev Multi-Beta Multi-Strategy (EW)	1.85%	3.66%
SciBeta Dev Multi-Beta Multi-Strategy (ERC)	3.09%	2.54%
FTSE RAFI Developed 1000 Index	13.75%	-6.56%
MSCI World Equal Weighted Index	6.09%	-3.51%
MSCI World Minimum Volatility Index	-1.89%	11.73%
Annual Excess Returns (over CW)	**Top 25% Quarters by LOW VOL factor returns**	**Bottom 25% Quarters by LOW VOL factor returns**
SciBeta Dev Multi-Beta Multi-Strategy (EW)	4.98%	-3.80%
SciBeta Dev Multi-Beta Multi-Strategy (ERC)	3.98%	-2.78%
FTSE RAFI Developed 1000 Index	-2.20%	6.59%
MSCI World Equal Weighted Index	-1.92%	6.91%
MSCI World Minimum Volatility Index	17.44%	-18.89%

EXHIBIT 4

Outperformance probability (over the broad CW benchmark) of the FTSE RAFI 1000 Developed Index, MSCI World Equal Weighted Index, MSCI World Minimum Volatility Index, FTSE Developed Diversified Factor Index, MSCI World Quality Mix Index, Scientific Beta Multi-Beta Multi-Strategy (EW) and Scientific Beta Multi-Beta Multi-Strategy (ERC). The analysis is based on daily total return data in USD from 12/31/2004 to 12/31/2014 (10 years). It is computed using a rolling window analysis with window length corresponding to the investment horizon (1/3/5 years) and one-week step size. The benchmark is the cap-weighted portfolio of all stocks in the investible universe. Data source: Bloomberg and www.scientificbeta.com.
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	Outperformance Probability 1Y	Outperformance Probability 3Y	Outperformance Probability 5Y
SciBeta Dev Multi-Beta Multi-Strategy (EW)	77.66%	97.27%	100.00%
SciBeta Dev Multi-Beta Multi-Strategy (ERC)	80.43%	99.73%	100.00%
FTSE RAFI Developed 1000 Index	52.55%	60.38%	67.18%
MSCI World Equal Weighted Index	59.15%	48.63%	90.46%
MSCI World Minimum Volatility Index	42.55%	77.05%	79.01%

EXHIBIT 5

The table shows the return and risk performance of the FTSE EDHEC-Risk Efficient U.S. index and its competitors: FTSE RAFI US 1000 index, MSCI Minimum Volatility index and S&P 500 Equal Weight index. All statistics are annualized and daily total returns from Nov. 23, 2009 to Dec.31, 2014 are used. Returns are in USD. The "Secondary Market U.S. Treasury Bills (3M)" is the risk-free rate in US Dollars for U.S. The cap-weighted benchmark is the SciBeta U.S. CW index. FTSE® is a registered trademark of the London Stock Exchange Plc and The Financial Times Limited. RAFI® is a registered trademark of Research Affiliates LLC. MSCI® is a registered trademark of MSCI Inc. S&P® and S&P 500® are registered trademarks of Standard & Poor's Financial Services LLC ("S&P"), a subsidiary of The McGraw-Hill Companies, Inc. Source: scientificbeta.com.

U.S. 11/23/2009 to 12/31/2014	Broad CW	FTSE EDHEC-Risk Efficient	FTSE RAFI	MSCI Min Vol	S&P 500 EW
Annual Returns	15.22%	18.43%	16.20%	15.93%	17.79%
Annual Volatility	15.82%	16.01%	16.60%	11.92%	17.54%
Sharpe Ratio	0.96	1.15	0.97	1.33	1.01
Maximum Drawdown	18.58%	19.11%	21.08%	13.98%	22.71%
Annual Relative Returns	-	3.21%	0.97%	0.71%	2.56%
Tracking Error	-	2.64%	2.20%	5.46%	2.85%
Information Ratio	-	1.21	0.44	0.13	0.90
95% Tracking Error	-	3.44%	2.44%	7.74%	3.82%
Maximum Relative Drawdown	-	4.22%	4.92%	12.04%	6.94%

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INDEXES

Long-Term Rewarded Equity Factors: What Can Investors Learn from Academic Research?

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The venerable "academic grounding"

Equity index products that claim to provide exposure to factors that have been well documented in academic research, such as value and momentum, among others, have been proliferating in recent years. Interestingly, providers across the board put strong emphasis on the academic grounding of their factor indexes[10]. It therefore appears useful to analyze what academic research has to say on equity factors to understand what we can learn from such research on designing or evaluating factor indexes. When analyzing academic publications on equity factor investing, three important lessons emerge, which are addressed in the sections below.

Lesson One: "Be serious with data"

When establishing which factors carry a reward by way of empirical analysis, it is important to understand that this is an almost daunting task. In fact, since Merton (1980), it is well known that we struggle to estimate expected returns reliably, simply because we rely on very few data points to estimate long-term expected returns: the starting price level and the end date price level. Of course, this is also true for factor returns.

Given this difficulty, when testing whether a factor carries a positive premium, academic research conducts a thorough assessment, including the analysis of very long-term data (covering time spans of at least 40 years), analysis across different regions and asset classes, and various corrections for possible data-mining biases. Importantly, these studies are open to criticism. Numerous papers are written to question previous empirical results (see, for example, the debate on the "low volatility puzzle"). For these reasons, academic research is much more capable of providing meaningful conclusions than a product backtest for a given factor index product. Even if a backtest is conducted very thoroughly by a product provider, it is hard to believe that the provider is able to conduct as thorough an analysis as the whole academic community, whose members have strong incentives not only to publish their own results but also to challenge the results of others by way of replicated tests. Therefore, factors that have undergone academic "validation" constitute a much stronger empirical justification than a mere product backtest.

The first important characteristic of empirical evidence on factor premia, as mentioned above, is that this evidence is derived based on tests applied to long-term data. 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 key factors with long-term U.S. data.

A second important characteristic of empirical research on factor premia is the assessment across different regions and asset classes. In fact, merely deriving a result from U.S. data, even if it holds in long-term data, does not allow the findings to be generalized to other geographic or investment contexts. From the standpoint of generalization, it is therefore interesting if results can be confirmed on equity markets for other geographies or even in entirely different 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 1

US evidence on equity factor premia

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

EXHIBIT 2

US evidence on equity factor premia

	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

A third important precaution empirical research takes before jumping to conclusions on the premium for a given factor is to adjust for data-mining or so-called "Multiple Testing." In fact, standard statistical tests are only valid when we test a given single hypothesis, such as that high book-to-market stocks carry a premium over low book-to-market stocks. However, in practice researchers may run several tests, for example trying out a large number of metrics until they find one that leads to significant results. This is also known as data-snooping or data-mining. To consider why such multiple testing may lead to false inference, consider a simple example. Assume you simulate data for 100 variables (potential "factors") that have zero mean. You would then expect to find about five variables with mean ("premium") significantly different from zero. This means that, even though the true mean ("premium") on all of the variables ("factors") is zero in the simulation, the statistical inference will tell you that some of the means are significantly positive, as long as you run enough tests.

In order to adjust for this problem, researchers have come up with tighter requirements for significance levels to take into account the possibilities of multiple testing. For example, Harvey, Liu and Zhu (2015) adjust t-ratios that are used for evaluating the significance of factor premia to take into account the fact that researchers have run many tests across hundreds of factors to document their premia. Interestingly, when applying these methods to standard equity risk factors, researchers find

[10] *For example, consider the following quotes from marketing material of index providers: "MSCI currently identifies six equity risk premia factors … . They are grounded in academic research …"; "In developing the Russell High Efficiency Factor Index series … we ensured that all of our factor specifications were consistent with academic research findings"; "The FTSE Global Factor Index Series is … designed to represent … factor characteristics for which there is a broad academic consensus"; ERI Scientific Beta: "factor indexes are meant to be investible proxies for rewarded factors that have been analyzed in the academic literature."*

that the main factors, such as value and momentum among others, remain statistically significant.

Despite the thorough evidence supporting the existence of premia for the main factors, there is continuous debate over the set of relevant equity factors. In fact, research often debates whether a factor has disappeared or a new factor has appeared. While questioning the baseline results and discussing relevant actors is obviously useful, investors in practice should be prudent before making abrupt changes to their set of factors or the associated investment beliefs. As mentioned before, the measurement of a risk premium is highly sensitive to the chosen sample (Merton 1980), and estimates of factor premia are subject to considerable uncertainty. Therefore, any conclusions based on empirical evidence should only be drawn from studying very long time periods, and conducting tests across different datasets. Moreover, any arguments in favor of the disappearance of standard factors or the appearance of new factors should not be investigated based on empirical evidence alone, but should also consider the underlying economic mechanisms, an issue we turn to in the next section.

Lesson Two: "Being serious with data is not enough"

In addition to convincing empirical evidence, the existence of a factor premium should be supported by a compelling economic rationale. 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."

To illustrate why the existence of an economic rationale is an important requirement for considering a factor to be rewarded, it is useful to take the equity market risk premium as an example. From an empirical perspective, the equity risk premium can be statistically indistinguishable from zero even for relatively long sample periods. However, economic reasoning suggests that stocks should have higher reward than bonds. Clearly, even if the premium for holding equity is well-documented empirically, investors are reluctant to hold too much equity due to its risks. Similar reasoning can be applied to additional equity risk factors. Instead of focusing only on the empirical evidence, investors' due diligence should look at why there should be a risk premium for a given factor in the first place. In other words, investors should ask what the economic rationale for a factor premium is, to form an opinion on its existence and persistence.

The existence of factor premia can be explained in two different ways — a risk-based explanation and a behavioral-bias explanation. The risk-based explanation premises that the risk premium is compensation to investors who are willing to take additional risk by being exposed to a particular factor. Additional risk exists when assets that correspond to a given factor tilt tend to provide poor payoffs in bad times, thus exposing investors to a risk of losses in times when their economic situation is already poor, their consumption is low, and marginal utility of consumption is high. The behavioral explanation conceives that the factor premia exist because investors make systematic errors due to behavioral biases such as overreaction or under-reaction to news on a stock.

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

If the risk premium can only be explained by behavioral reasoning, it is expected to disappear in the absence of limits to arbitrage. On the other hand, a risk factor with a strong rational or risk-based explanation is more likely to continue to have a premium in the future. Therefore, it is perhaps more reassuring for an investor to have a risk-based explanation.

We refer to Exhibit 3 for a brief list of risk-based and behavioral explanations of each factor.

Lesson Three: "Be practical"

A common criticism of academic research on factor premia is the supposed impracticality of academic factor definitions, simply because most results in academic research abstract from transaction costs and other implementation issues such as turnover. It is indeed the case that many academic studies do not necessarily aim to consider implementation issues. In fact, product providers often justify deviations from academic factors with implementation needs. But while early studies indeed abstract away from implementation issues, recent academic research addresses this shortcoming. In particular, recent research examines whether the premia to common equity risk factors survive net of transaction costs. Moreover, it assesses whether we can use mitigation strategies to ease implementation when harvesting these premia.

Novy-Marx and Velikov (2014) assess turnover and estimate transaction costs for common factor strategies. They find that the net-of-cost factor premia mostly remain significant. Exhibit 4 provides a summary of their findings.

In addition to assessing whether the returns to simple strategies are robust to transaction costs, research has tested adjusted implementations of factor premium strategies that try to ease implementation. Novy-Marx and Velikov (2014) test several such mitigation strategies and find that such approaches can substantially ease implementation while sustaining most of the return benefits, which often results in improvements in net of cost factor premia.

Frazzini, Israel and Moskowitz (2012) conduct a similar analysis and find that after taking into account realistic transaction costs, factor premia remain significant, especially when making adjustments to ease implementation: "We measure the real-world transaction costs and price impact function … and apply them to size, value, momentum, and short-term reversal strategies. … Strategies designed to reduce transaction costs can increase net returns and capacity substantially, without incurring significant style drift. We conclude that the main anomalies … are robust, implementable and sizeable."

Moreover, Amenc et al. (2012) provide a clear implementation framework for factor-tilted indexes in a long-only context with an aim of providing factor-tilted indexes which are not only implementable, but also well-diversified. Practical implementations of such well-diversified indexes lead to risk/return improvements over simple cap-weighted quintile portfolios[11], as well as considerable investibility improvements through lower turnover and fewer average days to trade at rebalancing (Amenc et al. 2015).

In summary, while much of the early evidence did not consider practical implementation issues, more recent research confirms that the standard factors lead to rewards even net of implementation considerations. Moreover, straightforward adjustments to strategy design that ease implementation lead to even more pronounced premia net of transaction costs. Therefore, there is a strong case that academically grounded factors can be used to design implementable strategies. Given this evidence, when considering deviating from academic factor definitions, investors should be careful to not throw out the baby (academic grounding) with the bathwater (unrealistic assumptions on implementation issues).

Conclusion: What "academic grounding" does not mean

The fact of the matter is that many factor-investing strategies and indexes offered by product providers create a considerable mismatch with academic definitions. Exhibit 5 provides an overview of factor definitions retained in several commercially available factor indexes and contrasts them with the Fama and French (2012, 2014) factor definitions, which are widely used in academic research that either tests the empirical evidence on these factors or assesses their economic rationale.

The mismatch between the provider definitions and the standard academic definitions is striking. While the Fama and French definitions rely on straightforward variables and make a

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

Net-of-cost factor premia, as reported by Novy-Marx and Velikov (2014).
Extracted from Novy-Marx and Velikov (2014). See their Table 3. All values are monthly. Factors based on cap-weighted decile portfolios. Portfolios are rebalanced annually for most factors but monthly for low idiosyncratic volatility and momentum. Factors are return differences between two extreme decile portfolios (cap-weighted). Time period is July 1963 to December 2013.

(Monthly)	Gross premium		Turnover	T-costs	Net premium	
	Avg.	[t-stat]			Avg.	[t-stat]
Size	0.33%	[1.66]	1.23%	0.04%	0.28%	[1.44]
Profitability	0.40%	[2.94]	1.96%	0.03%	0.51%	[3.77]
Value	0.47%	[2.68]	2.91%	0.05%	0.42%	[2.39]
Investment	0.56%	[4.44]	6.40%	0.10%	0.46%	[3.60]
Low Volatility	0.63%	[2.13]	24.59%	0.52%	0.11%	[0.37]
Momentum	1.33%	[4.80]	34.52%	0.65%	0.68%	[2.45]

[11] *On average across six well-documented factors, diversified multi-strategy indexes have a Sharpe ratio of 0.7 compared to an average Sharpe ratio of 0.56 for cap-weighted quintile portfolios.*

choice of selecting one key metric to come up with a factor score for each stock in a transparent and simple way, the proprietary definitions from providers use different sets of variables, as well as various adjustments, and often consist of complex combinations of several variables. For example, some factor scores are calculated relative to the industry or regional groups a stock belongs to. Some providers use such industry or region adjustments for certain variables within a given factor score while not using it for other variables making up the same factor score. Moreover, providers often use variables which are quite far removed from the original factor definition, such as the change in sales over total assets or the leverage in quality scores, as compared to the simple use of a profitability measure by Fama and French. Overall, the different index providers are in stark disagreement with how academic research defines these factors.

In general, such proprietary definitions increase the amount of flexibility providers have in testing many variations of factors and thus pose a risk of data-mining, and all the more so in that it remains unclear why these adjustments are made and in particular whether there are any fundamental economic reasons for using some of these variables and adjustments for a given factor. In fact, it appears that providers sometimes explicitly aim at selecting ad-hoc factor definitions which have performed well over short-term backtests. As an illustration, consider the following statements from white papers that select factor definitions for factor indexes based on backtesting various combinations of variables on a particular dataset spanning a time period of about 13 years[12]:

- "For each composite value index, factors are selected on the basis of the most significant t-stat values"
- "Our preferred measure of momentum is the Residual Sharpe Ratio, which displays relatively high risk-adjusted performance outcomes, and relatively low levels of volatility"

Moreover, some providers have launched "enhanced" factor indexes which replace the factor definitions in their standard factor indexes with new and improved recipes.

Of course, selecting proprietary combinations or making proprietary tweaks to variable definitions offers the possibility of improving the performance of a factor index in a backtest. The question is whether the improvement of the "enhanced" factor definition will also hold going forward, especially if there is no solid economic foundation for it. There is clearly a risk that one ends up with what academics have termed "lucky factors." Harvey and Liu (2015) show that by snooping through data on a large number of candidate factors and retaining those with the highest t-stat, one takes the risk of uncovering flukes, which will not repeat out of sample. Perhaps even more importantly, it is unclear what — if anything — factors with extensive proprietary tweaks still have in common with the factors from academic research. Therefore, the empirical evidence in favor of the academic factors and their economic grounding cannot be transposed to such new proprietary factors.

EXHIBIT 5

US evidence on equity factor premia

Provider	Value	Momentum	Quality
Fama-French	Price to Book	Past 12 Months return (omitting last month)	ROE (operating profits divided by book equity)
Goldman Sachs	Value score from proprietary risk model (Axioma) relative to stock's regional industry group	Residuals from cross-sectional	Composite based on asset turnover, liquidity, ROA, operating CF to assets, accruals, gross margin, leverage
MSCI Multi factor Indexes	Sector-relative composite based on Enterprise Value/Operating CF, Forward P/E, Price to Book	Composite score based on excess return divided by annual volatility over past 12 months and past six months	Composite based on return on equity, standard deviation of earnings, debt-to-equity
FTSE Global Factor Index Series	Composite based on cash flow to price, net income to price, and country-relative sales to price	Mean/Standard Deviation of "average residual" from 11 rolling window regressions of past 36 months returns on country and industry index	Composite based on operating CF to debt, net income to assets, annual change in (sales over assets), accruals
Deutsche Bank Equity Factor Indexes	Composite based on inverse of Enterprise Value to EBITDA and dividend yield	Twelve-month return (omitting last month) minus risk adjustment times idiosyncratic volatility score	Composite based on return on invested capital and net operating assets growth

In the absence of a clear relation with academic standard factors, such proprietary factor strategies are merely ad-hoc constructs resulting from product backtests. In fact, to find out whether any of these new proprietary factors are indeed related to the well-documented academic factors, one would first need to assess how they align empirically with standard factors. This point was also made clear by Eugene Fama in a recent interview, when on the topic of value factor and more proprietary versions of this factor he states, "Now everybody talks about value... . Some stuff is fly-by-night. There are like 45 versions of that and every guy has their own marketing ploy. The acid test is, you put it in the three-factor model and it says it is a value portfolio."

In the end, a minimum requirement for good practice in factor investing is to avoid creating a mismatch with academic factors. This can be achieved easily by referring to indicators for which academic research has provided thorough tests and economic explanations, and by refraining from proprietary "tweaks."

Alternatively, when using novel or proprietary factors, one needs to make sure that they are thoroughly tested (i.e., tested in very long-term data, across asset classes, for robustness to data-mining and to transaction costs) as well as linked to economic mechanisms. Of course it seems like a heroic objective for a product provider to aim to replicate the work that the whole academic community has been doing on standard factors, only to assess the robustness of his own proprietary factor. Therefore, one can make a reasonable case that proprietary factors may never be able to reach the amount of thorough testing that their standard academic counterparts benefit from.

Given the strong emphasis providers put on the "academic grounding" of their factor strategies, it is indeed surprising that they then chose to implement products which represent a gross mismatch with academic factor definitions and do not respect the key academic principle of parsimony. Instead of paying lip service to an "academic grounding" and coming up with a marketing innovation of tweaked factors, perhaps it is time that product providers actually used academic research in their product development. Moreover, investors should hold providers to high standards and conduct thorough due diligence on the soundness of particular implementations of factor investing

It is also worth emphasizing that a key idea behind the use of simple standard factors is to obtain robustness through parsimony. Parsimony refers to the idea that one can explain "a lot" with "a little." While proprietary factor definitions may be able to explain more in sample, they also pose a risk of picking up noise, which one can avoid with more parsimonious factor definitions such as the standard factors from the literature. The statistician George E. P. Box famously argued in favor of parsimony by writing that "overelaboration and over-parameterization is often the mark of mediocrity." Indeed, the parsimony of standard academic equity factor definitions may be preferable to overelaboration and over-parameterization of tweaked proprietary factors that are sometimes proposed by product providers. •

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[12] *As reported in the papers "Factor Exposure Indices – Value Factor" and "Factor Exposure Indices – Momentum Factor," recovered on July 1, 2015 at <http://www.ftse.com/products/downloads/FTSE_Value_Factor_Paper.pdf> and <http://www.ftse.com/products/downloads/FTSE_Momentum_Factor_Paper.pdf>.*

INDEXES

Concentrated vs. Diversified Factors

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Factor index construction: considering alternative approaches

With recent developments in risk-factor-based investing, many index providers, and more generally investment product providers, offer strategies that help investors to gain exposure to various identified risk factors, such as value, momentum and size, amongst others. While there is a consensus on the factors that are rewarded over the long term, it must be acknowledged that the implementation of factor investing, notably in the long-only universe, is not subject to the same consensus.

Exhibit 1 summarizes the alternative implementation approaches, namely concentrated or well-diversified factor indexes, also termed smart factor indexes (see Amenc et al. 2014). Concentrated factor indexes identify stocks that have a pronounced factor tilt for a given factor and aim to obtain strong exposure to this factor through a stock selection that is often restrictive, resulting in relatively few securities in the portfolio in terms of the nominal number of stocks. Moreover, the weighting scheme applied to the stock selection is either market cap-weighting or score-based weighting, resulting in a very uneven distribution of weights. Therefore, the effective number of stocks in the portfolio will also be low. The idea behind this approach is to maximize over the long term the return associated with the strongest exposure possible to the rewarded risk factor.

Smart factor indexes implement a relatively mild stock selection, where stocks with above-average exposure for a given factor are retained. In a second step, these stocks are weighted by a combination of diversification-based methods which aim to create a well-balanced portfolio in terms of weights and risks. The idea behind this approach is to reconcile the exposure to the right factor with avoidance of excessive portfolio concentration. Poor portfolio diversification exposes the investment to risks of excessive volatility over the short and medium term.

The objective of this article is to compare the results of smart factor indexes with several stylized examples of concentrated factor indexes. Before turning to the empirical comparison, a number of conceptual considerations are in order.

Products that aim to capture explicit risk-factor tilts through concentrated portfolios effectively neglect adequate diversification. This is a serious issue because diversification has been described as the only "free lunch" in finance. It allows a given exposure to be captured with the lowest level of risk required. In contrast, gaining factor exposures exposes investors to risk factors, and therefore, such exposures do not constitute a "free lunch." They instead constitute compensation for risk in the form of systematic factor exposures. Such capturing of risk premia associated with systematic factors is attractive for investors who can accept the systematic risk exposure in return for commensurate compensation.

However, factor-tilted strategies, when they are very concentrated, may also take on other, non-rewarded, risks. Non-rewarded risks come in the form of idiosyncratic or firm-level risk, as well as potential risk for sector concentration. Financial theory does not provide any reason why such risk should be rewarded. Therefore, a sensible approach to factor investing should not only look to obtain a factor tilt, but also at achieving proper diversification within that factor tilt. To illustrate this point, we focus on the value factor as an example below, but the discussion carries over to other factors, too.

In fact, if the objective was to obtain the most pronounced value tilt, for example, the only unleveraged long-only strategy that corresponds to this objective is to hold 100% in a single stock, the one with the largest value tilt, as measured for example by its estimated sensitivity to the value factor or its book-to-market ratio. This thought experiment clearly shows that the objective of maximizing the strength of a factor tilt is not reasonable.

Moreover, this extreme case of a strong factor tilt indicates what the potential issues with highly concentrated factor indexes are. First, such an extreme strategy will allow the highest possible amount of return to be captured from the value premium, but it will necessarily come with a large amount of idiosyncratic risk, which is not rewarded and therefore should not be expected to lead to an attractive risk-adjusted return. Second, it is not likely that the same stock will persistently have the highest value exposure within a given investment universe. Therefore, a periodically rebalanced factor index with such an extreme level of concentration is likely to generate 100% one-way turnover at each rebalancing

EXHIBIT 1

Concentrated vs. Diversified (Smart) Factor Indexes.

Concentrated Factor Tilts	• Do not consider any diversification objective. Ad hoc weighting schemes such as market cap-weighting or score-weighting are used. • Often select a very narrow universe of stocks with the highest exposure.
Diversified Factor Tilts	• Use a smart weighting scheme to ensure sufficient diversification while respecting liquidity and turnover constraints • Use a resonably broad universe of stocks that have above average exposure to the relevant factor.

EXHIBIT 2

Construction of Test Portfolios.
Note that Diversified Multi-Strategy is an equal weighted combination of five different weighting schemes: Maximum Deconcentration, Maximum Decorrelation, Maximum Sharpe Ratio, Minimum Volatility and Diversified Risk-Weighted.

	SciBeta Diversified Multi-Strategies	Cap-Weighted - 50% Stock Selection	Cap-Weighted - 20% Stock Selection	Score-Weighted - 50% Stock Selection	Score-Weighted - 20% Stock Selection
Universe	USA Long Term Track Records				
Number of Securites in the Universe	500				
Factor Analyzed	Mid-Cap, High Momentum, Low Volatility, Value, Low Investment and High Profitability				
Benchmark	Broad Cap-Weighted				
Reselection Frequency (Restoring Frequency)	Annual**				
Reweighting Frequency	Quarterly conditional upon turnover rules (on average the rebalancing frequency is 11-13 months)	Systematic Annual Rebalancing			
Stock Selection Criteria	Top 50% stocks based or corresponding factor values	Top 50% stocks based or corresponding factor values	Top quintile (20%) stocks based on corresponding factor values	Top 50% stocks based or corresponding factor values	Top quintile (20%) stocks based on corresponding factor values
Weighting Scheme	Diversified Multi-Strategy	Cap-weighted	Score-Weighted zscore of the values of the factor proxy varialbe is computed every year ad the sscore by taking the standard normal cumulative distribution value corresponding to the zscore. The sscore is used for stock selection and weighting.		

date, as the stock held previously in the strategy is replaced with a new stock that displays the highest current value exposure at the rebalancing date. While practical implementations of concentrated factor-tilted indexes will be less extreme than this example, we can expect problems with high levels of idiosyncratic risk and high levels of turnover whenever index construction focuses too much on concentration and pays too little attention to diversification.

Interestingly, the importance of diversification for a given factor tilt was outlined more than forty years ago in Benjamin Graham's famous book on value investing: "In the investor's list of common stocks, there are bound to be some that prove disappointing … . But the diversified list itself, based on the above principles of selection … should perform well enough across the years. At least, long experience tells us so." Aiming at a highly concentrated value portfolio would be completely inconsistent not only with financial theory, but also with the principles put forth by the early advocates of value investing.

Cap-weighted portfolios of value stock selections may at first seem to be more neutral implementations than score-weighted portfolios. However, it is well known that cap-weighting has a tendency to lead to very high concentration given the heavy tailed nature of the distribution of market cap across stocks in the same universe. It is well documented in the academic literature that simple cap-weighted value-tilted portfolios have not led to attractive performance. In fact, across different studies (see e.g., Fama and French, 2012, among others), empirical results show that a value strategy needs to be well-diversified to deliver a significant premium. For example, the standard Fama and French value factor includes a broad selection of stocks, and uses a two-tiered weighting approach to obtain better diversification. In particular, the value factor is an equal-weighted combination of sub-portfolios for different market cap ranges, effectively overweighting smaller size stocks and increasing the effective number of stocks. The fact that the most widely cited research documenting the relevance of the value factor does not use simple cap-weighted factors, but rather constructs more balanced portfolios, shows the lack of support for industry practices using simple cap-weighted factor indexes. For completeness, we may add that the literature does not use any score-weighted approaches either.

Overall, it thus appears that neither of the approaches that propose to construct concentrated factor indexes is supported by the academic literature, or for that matter, by common sense. However, how severe the challenges for concentrated factor index approaches are in practice is an empirical question we address below.

Data and methodology: construction of factor-tilted portfolios

We construct a total of 30 portfolios, representing five different tilt-design approaches for each of the six factor tilts — Mid Cap, Momentum, Low Volatility, Value, Investment and Profitability. We construct four different proxies for concentrated portfolios and compare these portfolios to well-diversified indexes that combine the diversified multi-strategy weighting scheme with a 50% stock selection, namely the Scientific Beta smart factor indexes for the same six factors. Both for the diversification strategy indexes and for the concentrated test portfolios, the factor scores are updated annually[13]. We test these competing approaches based on U.S. long-term data for a 40-year time period from January 1975 to December 2014, where the stock universe consists of the top 500 stocks by market cap. Exhibit 2 provides an overview of the different strategies we test.

Turnover

As discussed in our thought experiment in the introduction, it is clear that high levels of concentration potentially lead to severe turnover. Turnover will be high especially when the stock selection criteria move fast, leading to pronounced changes in eligible stocks for a given factor tilt from one rebalancing date to the next. Of course, intuition suggests that the turnover will depend on the severity of the stock selection screen.

Exhibit 3 reports the relative increase in turnover for concentrated portfolios compared to the well-diversified multi-strategy indexes for the same factor. The relative increase is calculated on the basis of annualized one-way turnover for the different diversified and concentrated strategies that we assess. One-way annual turnover is defined as:

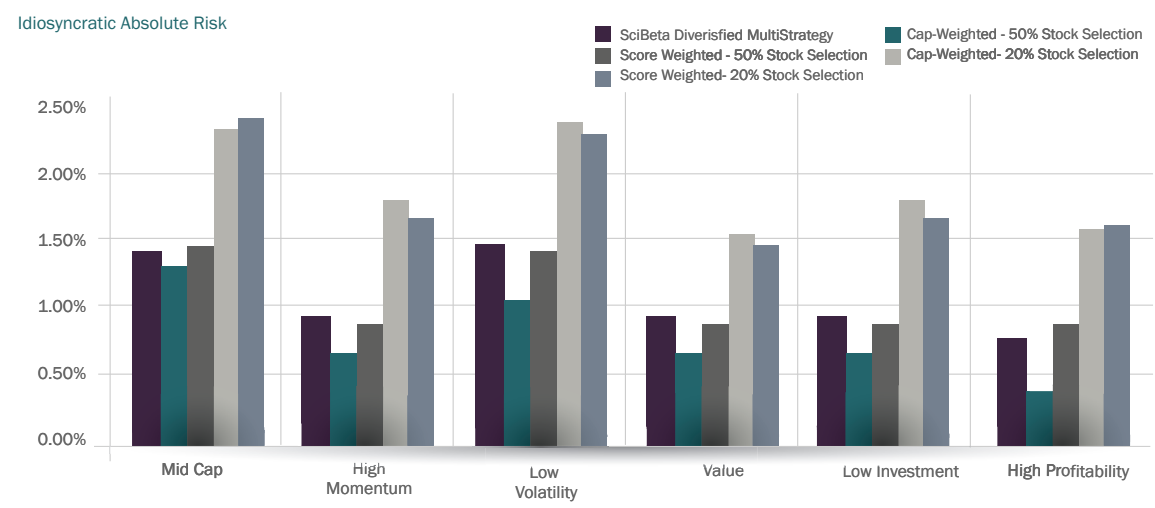
$$1\text{ - Way Ann Turnover} = \frac{1}{2}\sum_{i=1}^{n} \text{abs}(w_i^t - \hat{w}_i^{t-1})$$

EXHIBIT 3

Increase in turnover for concentrated factor indexes, relative to well-diversified indexes.
The analysis is based on daily total return data from 12/31/1974 to 12/31/2014 (40 years). Mid Cap, High Momentum, Low Volatility, Value, Low Investment and High Profitability selections represent 50%/20% of stocks with such characteristics in a U.S. universe of 500 stocks. The full names of the U.S. indexes used are: SciBeta United States Mid-Cap Diversified Multi-Strategy, SciBeta United States High-Momentum Diversified Multi-Strategy, SciBeta United States Low-Volatility Diversified Multi-Strategy, SciBeta United States Value Diversified Multi-Strategy, SciBeta United States Low Investment Diversified Multi-Strategy and SciBeta United States High Profitability Diversified Multi-Strategy. Source: www.scientificbeta.com/

EXHIBIT 4

Idiosyncratic volatility for concentrated and diversified factor indexes.
The analysis is based on daily total return data from 12/31/1974 to 12/31/2014 (40 years). Mid Cap, High Momentum, Low Volatility, Value, Low Investment and High Profitability selections represent 50%/20% of stocks with such characteristics in a U.S. universe of 500 stocks. In order to compute Carhart four-factor exposures and the volatility attribution to these factors, market, size, value and momentum factors for the U.S. universe available online at Kenneth French data library is used. The full names of the U.S. indexes used are: SciBeta United States Mid-Cap Diversified Multi-Strategy, SciBeta United States High-Momentum Diversified Multi-Strategy, SciBeta United States Low-Volatility Diversified Multi-Strategy, SciBeta United States Value Diversified Multi-Strategy, SciBeta United States Low Investment Diversified Multi-Strategy and SciBeta United States High Profitability Diversified Multi-Strategy. Source: www.scientificbeta.com.



It is clear from the results in Exhibit 3 that turnover tends to increase dramatically with higher concentration. For example, turnover for the value strategies reaches levels of the order of 40% for both score-weighted and cap-weighted portfolios with a 20% selection screen, while turnover is close to 20% for the strategies based on broader selections. We also observe a tendency for score weighting to lead to higher turnover than cap-weighting for a similar stock selection approach.

These results provide strong support for the problems outlined on a conceptual level above. Narrowing down the stock universe to obtain strong factor tilts severely increases turnover, thus leading to strategies which are more difficult and costly to implement than strategies based on broader selections.

Idiosyncratic risk

Increasing concentration is also expected to lead to an increase in unrewarded, idiosyncratic risk. We assess this issue by regressing returns of the factor strategies onto the standard Carhart (1997) factors, including the market, size, value and momentum factor. The idiosyncratic risk is then measured as the volatility of the residual return relative to the systematic return component which results from the factor exposures.

Exhibit 4 provides an overview of the estimated idiosyncratic volatility for the different index construction approaches across the six factor tilts.

Exhibit 4 provides strong evidence that idiosyncratic volatility increases with higher concentration. Note that financial common sense suggests that idiosyncratic risk should be diversified away! This confirms that many concentrated indexes are often exposed to risks that are not only unrelated to the factor tilts that they are intended to capture but also likely to be unrewarded over the long term.

Performance

The results discussed thus far show that increasing concentration comes with important challenges in terms of higher turnover. Given this additional implementation challenge and potential drag in terms of transaction costs on highly concentrated factor indexes, concentrated factor indexes would need to lead to marked improvements in performance. An open question would then be whether such performance improvements would lead to any practical improvements on a

[13] *The only exception is the Scientific Beta Momentum Diversified Multi-Strategy index, where the momentum score is updated semi-annually.*

net-of-cost basis, after taking into account high turnover and ensuing transaction costs.

However, the evidence suggesting increases in idiosyncratic risk for concentrated indexes casts some doubt on their capacity to truly increase risk-adjusted returns even on a before-cost basis. To verify what the comparative performance features of the various indexes are, we provide an overview on risk-adjusted performance in terms of the Sharpe ratio in Exhibit 5. The results in Exhibit 5 clearly suggest that concentrated indexes do not lead to higher Sharpe ratios than multi-strategy indexes.

In fact, across the six factor tilts, the performance and risk statistics suggest that — relative to multi-strategy factor indexes — highly concentrated factor-tilted approaches (e.g., 20% stock selection with cap-weighted or score-weighted) lead to higher volatility, especially for the score-weighted approach (the only exception is the low-volatility tilt). Concentration in the top quintile portfolios does not lead to any consistent improvement in Sharpe ratio, either. Multi-strategy indexes, on the other hand, owing to better diversification, minimize the unrewarded risks and thus have better Sharpe ratios. On average across the six factors, the multi-strategy indexes have a Sharpe ratio of 0.7 compared to, e.g., an average Sharpe ratio of 0.56 for the cap-weighted top quintile indexes. Therefore, the increase in implementation challenges does not lead to any meaningful performance improvement (even before considering implementation costs).

Investibility

To further assess the implementation aspects of concentrated and diversified factor indexes, we provide an overview of the days to trade at an average rebalancing date for a USD 1bn investment. In particular, we report as "Days to Trade" the number of days necessary to trade the total stock positions, assuming USD 1bn AUM and that 100% of the average daily dollar traded volume can be traded every day. Due to data availability, the period for this analysis is restricted to the last 10 years of the sample for the Scientific Beta U.S. indexes.

Exhibit 6 shows days to trade for each of the design approaches across six different factor tilts.

It is clear from Exhibit 6 that "Days to Trade" increases tremendously with a rise in concentration. Indeed, it is perhaps not surprising that rebalancing of very concentrated portfolios leads to strong implementation hurdles.

This finding confirms the implementation hurdles that were apparent from the analysis of turnover, but also shows that when considering the available trading volume in stocks whose rebalancing generates this turnover, the implementation problems of concentrated approaches compared to well-diversified approaches actually increase on a relative basis.

In fact, relative to the multi-strategy indexes, and on average across the six factors, the score-weighted top 20% indexes have on average more than 30% higher turnover, and more than 100% higher average days to trade. Clearly, concentrated factor tilts pose real challenges of investibility.

CONCLUSIONS

Factor indexes are a potentially value-adding tool. Investors can expect benefits from relying on indexes that tilt toward well-documented factors, which carry sizeable and repeatable return benefits over long investment horizons. However, when aiming to implement the insight from empirical finance that certain factors lead to premia, one should not forget a perhaps even more fundamental insight from financial theory: the idiosyncratic risk of over-concentrating a portfolio is not rewarded. Our results suggest that index construction approaches that build diversified portfolios for a given factor tilt are exposed to less unrewarded risk. Considering these two aspects, factor tilts and diversification, should be an integral part of a sensible factor index design methodology. Moreover, factor indexes are indexes, and thus should be implementable with ease and low turnover. Our results suggest that increasing concentration leads to high turnover levels and real investibility hurdles that are not compensated by any performance advantages. •

EXHIBIT 5

Sharpe ratios for concentrated and diversified factor indexes.
The analysis is based on daily total return data from 12/31/1974 to 12/31/2014 (40 years). Mid Cap, High Momentum, Low Volatility, Value, Low Investment and High Profitability selections represent 50%/20% of stocks with such characteristics in a U.S. universe of 500 stocks. Yield on Secondary U.S. Treasury Bills (3M) is used as a proxy for the risk-free rate. The full names of the U.S. indexes used are: SciBeta United States Mid-Cap Diversified Multi-Strategy, SciBeta United States High-Momentum Diversified Multi-Strategy, SciBeta United States Low-Volatility Diversified Multi-Strategy, SciBeta United States Value Diversified Multi-Strategy, SciBeta United States Low Investment Diversified Multi-Strategy and SciBeta United States High Profitability Diversified Multi-Strategy. Source: www.scientificbeta.com.

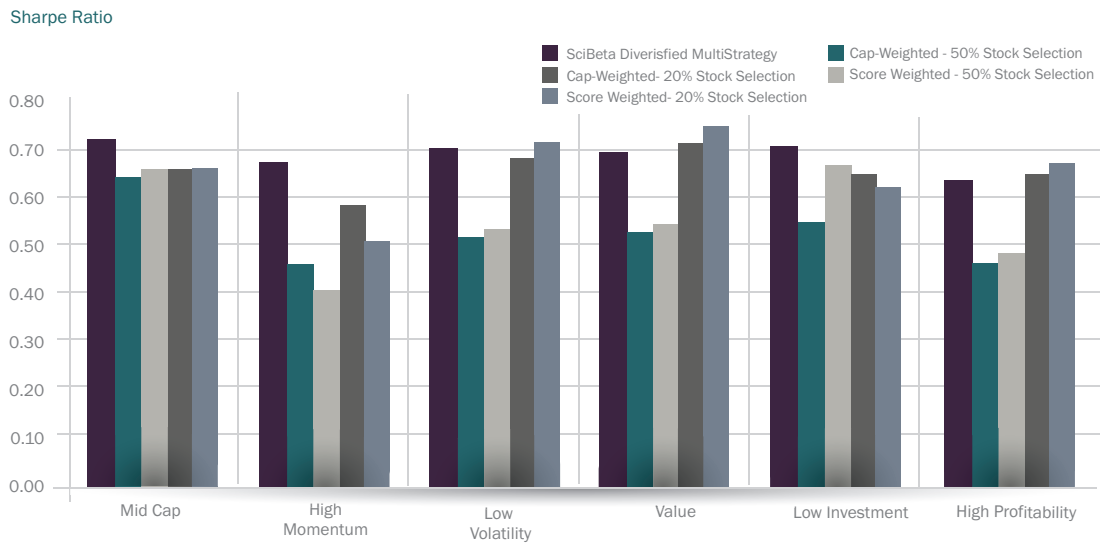
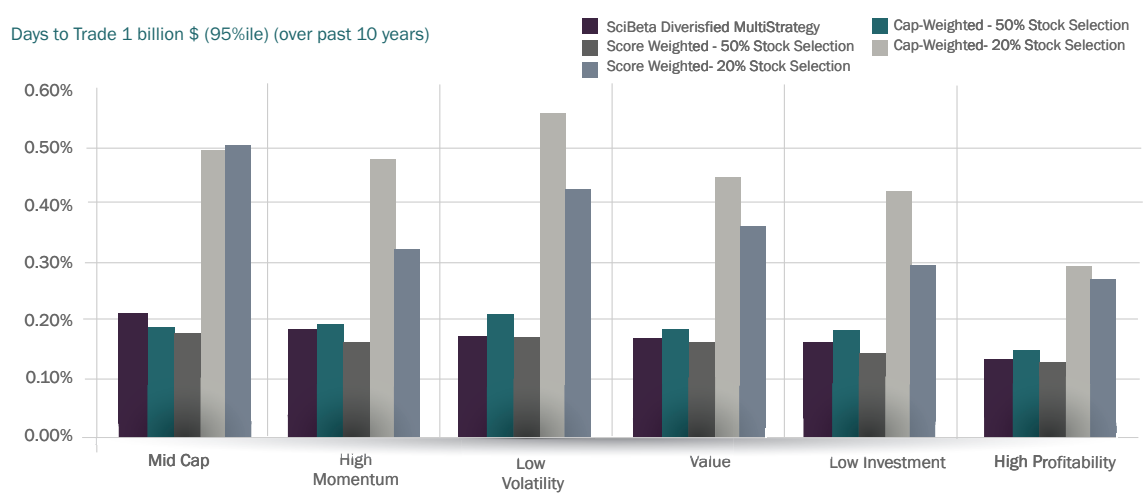


EXHIBIT 6

Days to trade a USD 1bn investment for concentrated and diversified factor indexes.
The analysis is based on weights of total return indexes on every rebalancing date for the time period 12/31/2004 to 12/31/2014 (10 years). Mid Cap, High Momentum, Low Volatility, Value, Low Investment and High Profitability selections represent 50%/20% of stocks with such characteristics in a U.S. universe of 500 stocks. Yield on Secondary U.S. Treasury Bills (3M) is used as a proxy for the risk-free rate. The broad cap-weighted index based on the 500 largest stocks in the U.S. universe is used as the benchmark. The full names of the U.S. indexes used are: SciBeta United States Mid-Cap Diversified Multi-Strategy, SciBeta United States High-Momentum Diversified Multi-Strategy, SciBeta United States Low-Volatility Diversified Multi-Strategy, SciBeta United States Value Diversified Multi-Strategy, SciBeta United States Low Investment Diversified Multi-Strategy and SciBeta United States High Profitability Diversified Multi-Strategy. Source: www.scientificbeta.com. "Days to Trade" is the number of days necessary to trade the total stock positions, assuming USD 1bn AUM and that 100% of the average daily dollar traded volume can be traded every day. Due to data availability, the period is restricted to the last 10 years of the sample for the Scientific Beta U.S. indexes.



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INDEXES

Factor Investing—Welfare Improving or Marketing Fad?

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A new approach known as factor investing has recently emerged in investment practice, which recommends that allocation decisions be expressed in terms of risk factors, as opposed to standard asset class decompositions. While intuitively appealing, this approach poses a major challenge, namely the choice of the meaningful factors and the corresponding investible proxies.

Simply put, factor investing proposes to regard each constituent in an investor's portfolio, and therefore the whole portfolio, as a bundle of factor exposures. Obviously, factor models, such as those of Sharpe (1963) and Fama and French (1993), have long been used for performance measurement purposes, and several factors correspond to classical investment styles, such as value-growth investing, trend following or short volatility, that were in use in the industry before they were formally identified as asset pricing factors. In this context, the question arises as to whether factor investing is truly a new welfare-improving investment paradigm or merely another marketing fad.

A first remark is that if there are as many factors as individual securities and the factors are themselves portfolios of such securities, then thinking in terms of factors is strictly equivalent to thinking in terms of asset classes, and therefore would not add any value. More relevant is the situation where a parsimonious factor model is used, with a number of factors smaller than the number of constituents. The first challenge posed for investors who decide to express their decisions in terms of factor exposures is then the identification of meaningful factors. In this perspective, the theoretical section of recent research[14] that we have conducted as part of the Lyxor "Risk Allocation Solutions" research chair at EDHEC-Risk Institute reviews the academic literature on asset pricing and makes a list of conditions that such factors should satisfy. We then survey a (vast) empirical literature in order to identify the most consensual factors in three major asset classes, namely stocks, bonds and commodities.

The second challenge in factor investing is the implementation of decisions in a cost-efficient way with investible proxies. On the empirical front, our paper provides an analysis of the welfare gains that can be expected from the use of proxies for factors, and discusses the choice of long-only vs. long-short factors, which is relevant for many investors given that they are not allowed to take short positions.

In asset pricing theory, the relevant and important factors are the "pricing factors," the exposures to which explain all differences in expected returns across assets.

Asset pricing theory makes a distinction between "pricing factors," which explain differences in expected returns across assets, and "priced factors," which earn a premium over the long run. The theory, exposed in the textbooks of Duffie (2001) and Cochrane (2005), expresses the risk premium on an asset, i.e., the expected return on this asset in excess of the risk-free rate, as a function of the covariance between the payoff and an abstract quantity known as the stochastic discount factor. The goal of theoretical and empirical asset pricing models is to find a representation for this random variable in terms of economically interpretable variables. For instance, in consumption-based models, the stochastic discount factor is proportional to the marginal utility of consumption. This conveys an important economic intuition: risk premia exist as rewards required by investors in exchange for holding assets that have a low payoff in "bad times," defined as times where investors' wealth is low and marginal utility is high.

EXHIBIT 1

Cap-weighted equity factor indexes as substitutes for equity sector indexes (1975-2013).

Universe	Avg. return%	Volatility (%)	Sharpe Ratio	Tracking Error(%)	Infomation Ratio	Ann. 1-way Turnover (%)
			EQUALLY WEIGHTED			
Equ 10s	12:56	16:37	0:45	2:82	0:34	8:9
Equ-L/O-4	13:23	16.73***	0:48	2:59	0:63	3:5
			MINIMUM VARIANCE			
Equ 10s	12:67	14:26	0:52	6:18	0:17	29:1
Equ-L/O-4	12.06	15.87***	0.43	3.48	0.13	27:2
			RISK PARITY			
Equ 10s	12:76	15:60	0:48	3:64	0:32	11:9
Equ-L/O-4	13:17	16:60***	0:48	2:64	0:60	4:6
			FACTOR RISK PARITY			
Equ 10s	12:76	14:18	0:53	5:58	0:21	34:6
Equ-L/O-4	12:55	15:68***	0:47	3:59	0:27	26:2
			MINIMUM TRACKING ERROR			
Equ 10s	11:98	16:97	0:40	1:47	0:27	14:0
Equ-L/O-4	12:59	16:60***	0:44	1:99	0:50	15:3
			RELATIVE RISK PARITY			
Equ 10s	11:98	16:96	0:40	1:47	0:26	13:2
Equ-L/O-4	12:62	16:65***	0:44	1:97	0:52	11:2
			RELATIVE FACTOR RISK PARITY			
Equ 10s	12:45	16:52	0:44	2:64	0:33	38:1
Equ-L/O-4	12:63	16:72***	0:44	2:10	0:50	17:5

Note: The tracking error and the information ratio are computed with respect to the broad cap-weighted index. *** denotes significance of the difference with respect to the benchmark at the 1% level.

Pricing factors arise when one attempts to find observable proxies for the aggregate investor's marginal utility. In a factor model, the risk premium on an asset is a linear combination of the factor risk premia, weighted by the betas of the asset with respect to the factor. As a consequence, all alphas are zero and the cross-sectional differences between expected returns are entirely explained by the differences in factor exposures. As for an asset, the premium of a factor is determined by its covariance with the stochastic discount factor, so that a factor deserves a positive premium if, and only if, it is high in "bad times" and low in "good times." A factor is said to be "priced" if it has a non-zero premium. It can be shown that there is no loss of generality from searching for pricing factors among returns, but further assumptions are needed to identify their economic nature. Two main classes of theoretical models have been developed to this end. A first category uses economic equilibrium arguments. In the static Capital Asset Pricing Model (CAPM) of Sharpe (1964), the only factor, or "market factor," is the return on aggregate wealth. The intertemporal version (ICAPM) of Merton (1973) adds as new factors the variables that predict changes in expected returns and volatilities. A second class of models refers to the Arbitrage Pricing Theory (APT) of Ross (1976) and characterizes factors as variables that explain returns from a statistical standpoint. One of the questions studied in the recent asset pricing literature is whether the factors proposed in empirical asset pricing models do meet these theoretical criteria.

The property that assets have zero alphas with respect to the factors has an interesting implication. It can be shown that a theoretical single-step solution to a mean-variance optimization problem coincides with an optimal linear combination of mean-variance efficient benchmark portfolios invested in individual securities if each individual security has a zero alpha when regressed on the benchmark portfolios. This result therefore suggests that the most meaningful way for grouping individual securities is not by forming arbitrary asset class indexes, but instead by forming factor indexes, that is, replicating portfolios for a set of indexes that can collectively be regarded as linear proxies for the unobservable stochastic discount factor, thus providing a theoretical justification for factor investing.

Empirically, the search for pricing factors in asset classes such as stocks, bonds and commodities begins with the identification of persistent and economically interpretable

[14] *Martellini L. and V. Milhau, July 2015, Factor Investing: A Welfare Improving New Investment Paradigm or Yet Another Marketing Fad? EDHEC-Risk Institute Publication produced as part of the Lyxor "Risk Allocation Solutions" research chair at EDHEC-Risk Institute.*

patterns in average returns. Recent research has subsequently started to look for multi-class factors.

While the CAPM is relatively explicit about the nature of the underlying pricing factor (the return on aggregate wealth), multi-factor models derived from the ICAPM or the APT do not provide an explicit definition of their factors. Thus, the traditional approach in empirical asset pricing has been to examine the determinants of cross-sectional differences in expected returns and to find sound economic interpretations for regular patterns (presence of a risk factor, market frictions or behavioral biases).

Most of the empirical asset pricing literature has focused on factors explaining equity returns. This literature starts in the early 1970s with empirical verifications of the CAPM and concludes that the model's central prediction, namely the positive and linear relationship between expected excess return and the covariance with aggregate wealth, is not well validated by the data for two reasons. First, there exist patterns, or "anomalies," that are not explained by the market exposure, and second, the relation between expected returns and the market betas is at best flat, or even negative. The most consensual patterns are those that have shown to be robust to various statistical tests, to exist in almost all international equity markets, to persist over time, in particular after their discovery, and to admit plausible economic explanations. They include the size and value effects, which are historically among the first reported anomalies: small cap stocks tend to outperform their large cap counterparts, and there is a positive relationship between the book-to-market ratio and future average returns. The size and value factors are used together with the market factor in the model of Fama and French (1993). Another remarkably robust pattern is the momentum effect: the winners (resp., losers) of the past three to 12 months tend to outperform (resp., underperform) over the next three to 12 months. The number of reported empirical regularities has grown fast in the recent literature, and a survey by Harvey et al. (2013) lists at least 315 of them. Among them is the controversial "low volatility puzzle," namely the documented outperformance of low volatility stocks over high volatility stocks, the existence and persistence of which remains somewhat debated in the academic literature. Among the other noticeable patterns are the investment and profitability effects.

In fixed income, the two main traditional factors are term and credit. As put by Fama and French (1993), unexpected changes in interest rates and in the probability of default are "common risk factors" for bonds, so it is expected that they should be rewarded. Given that long-term bonds are more exposed to interest rate risk than short-term bills through their longer duration, one expects them to earn higher returns on average. Similarly, defaultable bonds are expected to earn a premium over default-free ones because default events are more likely to happen in bad economic conditions. However, a mathematical decomposition of the term premium, such as those performed in the studies of bond return predictability, suggests that it varies in sign and magnitude with changes in the slope of the term structure and changes in expectations about future interest rates. Historical evidence confirms this variation. In addition to these two standard factors, recent literature has found patterns similar to those encountered in the equity class, such as momentum, value (which refers to a long-term reversal effect) and low risk.

For commodities, one can obtain a first important factor by examining the determinants of the performance of passive strategies that roll over futures contracts. Research has shown that the long-term returns to such strategies are mainly driven by the roll returns, which are the positive or negative returns earned by replacing the nearest contract with the second nearest when the former matures. Hence, the prevailing shape of the term structure of futures prices is an essential determinant of long-term returns. Specifically, backwardated futures markets (for which the term structure is decreasing) outperform contangoed futures markets (for which it is increasing). This calls for the introduction of a term structure factor defined as the excess return of backwardated contracts over contangoed contracts. A related factor is the hedging pressure, which is suggested by the eponymous theory and indirectly captures the shape of the term structure. Beyond these "fundamental" factors, a momentum factor has also been empirically reported for commodities.

A class-by-class study reveals that some patterns exist repeatedly in various classes. Asness et al. (2013) show that this is the case for short-term momentum and long-term reversal in equities, bonds, commodities and currencies. Furthermore, the single-class momentum factors are positively correlated, and the same goes for value factors. Taken together, these findings justify a new approach, which is the construction of multi-class value and momentum factors, obtained by aggregating the corresponding single-class components.

Empirical tests show that investible proxies for factors add value in single-class or multi-class portfolios when they are used as complements or substitutes for broad asset class indexes. Moreover, in the equity class, a portfolio of factor indexes dominates a portfolio of sector indexes.

Our empirical study focuses on the following factors, which have been selected because they have well-documented historical performance, are theoretically grounded and are widely accepted by practitioners: size, value, momentum and volatility for equities; term and credit for bonds; and term structure and momentum for commodities. In addition, we test multi-class value and momentum factors computed after the methodology of Asness et al. (2013). A first analysis of the descriptive statistics for these factors highlights a few simple but important facts. Each long-only factor outperforms its opposite tilt, in line with the theoretical and empirical literature, and outperforms the corresponding broad asset class index. Correlations within a class are high (above 75%), although they are lower across classes, and they are much lower for long-short versions of the factors.

The benchmark universes that we consider contain the broad indexes of one or more asset classes, which represent the market factors. For equities, we also test the benefits of using a standard sector classification, as an alternative to grouping securities according to their factor exposures. A first method for assessing the usefulness of factors is to compare the efficient frontiers in the benchmark universe and in an extended universe that also contains the factors. Formal mean-variance spanning tests (see Kan and Zhou, 2012) reject the null hypothesis that the efficient frontier of the benchmark universe is included in that of the extended universe for all long-short factors and for most long-only factors. This is first evidence that the introduction of factors improves the efficient frontier, even though these tests rely on in-sample long-short efficient frontiers, so that they may give an overly optimistic picture.

For this reason, we also conduct a series of out-of-sample tests, where we compare portfolios of traditional indexes (asset class indexes or equity sectors) and portfolios of factors, by imposing long-only constraints and by estimating parameters without a look-ahead bias. Since a test of the relevance of factor investing is a joint test of the relevance of the chosen factors and the chosen allocation methodology, we run the comparison for various diversification schemes that avoid the estimation of expected returns: equally weighted, minimum variance, risk parity and "factor risk parity," where the implicit factors extracted from the covariance matrix. The "relative" counterparts of these schemes, which focus on the tracking error as opposed to the absolute volatility, are also tested. Exhibit 1 shows a sample of results for the equity class: for most weighting schemes, the four-factor portfolios have higher average return, higher Sharpe ratio and higher information ratio compared to their 10-sector equivalents. In addition, they have a lower turnover. Exhibit 2 extends the analysis to a multi-class context by comparing "policy-neutral" portfolios of equity, bond and commodity factors to a fixed-mix policy portfolio of 60% equities, 30% bonds and 10% commodities. Again, both the average return and the Sharpe ratio are improved.

` As a conclusion, there exist theoretical arguments in favor of factor investing, i.e., in favor of grouping individual securities into factor indexes as opposed to arbitrary forms of indexes. Extensive empirical literature has documented a number of recurring patterns in the returns of equities, bonds and commodity futures, and provides investors with a rich list of insights regarding the choice of meaningful factors in each of these classes. The identification of a parsimonious set of factors capturing the largest possible number of sources of risk is an ongoing task on the academic side. On the practical side, a challenge is to develop factor indexes that aim to capture factor risk premia at reasonable implementation costs. It is being addressed in the equity class with a new generation of "smart beta" indexes, but similar products are not as widely developed in other classes and no multiple-class products are available to date. •

EXHIBIT 2

Substitution of asset class indexes by factor indexes in policy portfolio (1988-2011).

Universe	Avg. Return%	Volatility (%)	Sharpe Ratio	Tracking Error(%)	Infomation Ratio
Policy portfolio	8:82	9:44	0:52	0:00	-
	ABSOLUTE WEIGHTING SCHEMES				
MDC L/O-8	9:90*	9:46	0:63*	2:57	0:42
GMV L/O-8	9:54	8:78***	0:64	3:22	0:22
MENCB L/O-8	9:37	9:56	0:57	2:68	0:21
MENUB L/O-8	9:76	8:82***	0:66	3:55	0:26
	RELATIVE WEIGHTING SCHEMES				
MTE L/O-8	9:74*	9:24	0:63*	2:23	0:41
MENRCB L/O-8	9:56	9:57	0:59	2:90	0:25
MENRUB L/O-8	9:67*	9:36	0:62*	2:25	0:38

Note: MDC, MENCB and MENUB are the respective equivalents of equally-weighted, risk parity and factor risk parity with policy constraints. Similarly, MENRCB and MENRUB are the policy-neutral equivalents of relative risk parity and relative factor risk parity. *** (resp., *) denotes significance of the difference with respect to the benchmark at the 1% (resp., 10%) level.

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