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RESEARCH FOR INSTITUTIONAL MONEY MANAGEMENT

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or by e-mail to melanie.ruiz@scientificbeta.com

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INTRODUCTION

Noël Amenc
Professor of Finance, EDHEC Business School
Director, EDHEC-Risk Institute
and CEO, ERI Scientific Beta

I am pleased to present the latest issue of the Research for Institutional Money Management supplement to P&I, which aims to provide institutional investors with an academic research perspective on the most relevant issues in the industry today.

We begin by examining the role of two separate equity risk factors related to balance sheet characteristics: Low Investment and High Profitability. These factors rely on straightforward and parsimonious indicators, and can be expected to provide more robust performance benefits than ad-hoc stock picking indicators of "quality" used in the industry. Further value can be added by allocating across these two factors to exploit the low correlation across factor returns. Such combinations of the smart factor indexes for high profitability and low investment have led to improved performance compared to various commercial indexes which are based on ad-hoc definitions of "quality."

We then explore the economic rationale behind the various "factors" in the equity space. Rather than accepting new factors based on back-tested performance improvements, investors may be better advised to assess the theoretical groundings behind a factor. Having a convincing explanation should be a key requirement for investors when they decide to gain exposure to a given factor, as a theoretical justification of an observed effect provides some safeguard against data-mining.

We examine the claim that that all smart beta strategies generate positive value and small-cap exposure similar to that generated by any random portfolio strategy, and that the inverse of such strategies perform similarly or better. Our results are not supportive of the "monkey portfolio" argument (derived from Burton Malkiel's reference to how a monkey would perform when randomly selecting stocks for a portfolio). We find that various smart beta strategies display pronounced differences in factor exposures and performance characteristics. We also obtain a reassuring finding that inverting a portfolio strategy does not, in general, lead to the same performance as the original.

Alternative equity beta investing has clearly been the focus of increasing attention in the industry recently. Though products in this segment currently represent only a fraction of overall assets, there has been tremendous growth recently in terms of both assets under management and new product development. In this context, EDHEC-Risk recently carried out a survey among a representative sample of investment professionals to identify their views and uses of alternative equity beta. The article in this supplement presents the main results of this survey, which was drawn from the Newedge research chair at EDHEC-Risk Institute.

Traditionally, performance and risk reports for equity portfolios report a breakdown of portfolio holdings by geography, based on simple markers such as the stock's primary listing and the firm's place of incorporation and headquarters. However, it is questionable whether these markers are relevant for the underlying geographic exposure of a stock. For example, should an automaker who is listed, headquartered and incorporated in Germany, and sells his cars mainly to the U.S. and China, be considered as providing exposure to Germany, or even to Europe? In our article, drawn from research from the CACEIS "New Frontiers in Risk Assessment and Performance Reporting" research chair at EDHEC-Risk Institute, we analyze the usefulness of a company's reported geographic segmentation data in performance reporting.

Given the importance of estimating the performance of infrastructure debt instruments for both long-term investors and prudential regulators, we discuss the creation and implementation of the first robust valuation, risk measurement and data collection framework for private infrastructure project loans as part of the Natixis research chair at EDHEC-Risk Institute on the "Investment and Governance Characteristics of Infrastructure Debt Instruments."

We also propose the first valuation framework dedicated to privately held infrastructure equity investments, in research drawn from the work of the Meridiam/Campbell Lutyens research chair at EDHEC-Risk Institute. We develop a framework that takes into account the challenges of valuing privately held and seldom-traded infrastructure equity investments, with the aim of designing a methodology that can be readily applied given the current state of empirical knowledge and, going forward, at a minimum cost in terms of data collection.

Continuing in the alternative investment arena, we examine the possibility of measuring the capacity of a fund of hedge fund manager to manage risk efficiently. Most fund of hedge fund managers claim to do so. In order to reduce the dimension of the fund of hedge fund selection problem, and identify those who actually do, a new tactical style allocation factor is proposed — the X-Factor — that is designed with the objective of capturing the benefits of such active risk management.

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

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

Noël Amenc
Professor of Finance

Frédéric Blanc-Brude
Research Director

Romain Deguest
Senior Research Engineer

Felix Goltz
Head of Applied Research

Kumar Gautam
Quantitative Equity Analyst

Nicolas Gonzalez
Senior Quantitative Analyst

Majid Hasan
Research Assistant

Véronique Le Sourd
Senior Research Engineer

Ashish Lodh,
Senior Quantitative Analyst

Sivagaminathan Sivasubramanian
Quantitative Analyst

Mathieu Vaissié
Research Associate

PORTFOLIO MANAGEMENT

The Dimensions of Quality Investing: High Profitability and Low Investment Factors

Ashish Lodh
Senior Quantitative Analyst
ERI Scientific Beta

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

Sivagaminathan Sivasubramanian
Quantitative Analyst
ERI Scientific Beta

Quality stock picking vs. factor investing

Asset managers and index providers are increasingly touting the benefits of quality investing. Such strategies tilt portfolios to "high quality" stocks, as characterized, for example, by high profitability, stable earnings or low leverage, to name just a few of the variables used in practice. However, asset managers and index providers do not use a common definition of "quality," and a large variety of approaches exist. The premise of quality investing is that high quality stocks are not recognized by the market to a sufficient extent to increase their price to a level that fully reflects their superior quality — therefore such stocks offer a good investment opportunity. The concept has been traced back to fundamental stock pickers such as Benjamin Graham and Jeremy Grantham. De facto, systematic filters proposed today by many index providers aim to procure alpha in competition with traditional asset managers, without necessarily having all the same characteristics, and notably the capacity to take account of forecasts on evolutions in stock characteristics or new factors that can change the perception of those characteristics.

For academics and the proponents of a beta, rather than alpha, approach, which in our view is the only approach that is compatible with indexed investment management, the quality term refers to a completely different dimension: the factor approach.

Rational factor investing does not rely on finding underpriced stocks, but rather seeks to identify factors which lead to systematic risks which investors are unwilling to bear without a commensurate reward. It does not therefore require an ability to pick stocks by processing information in a better way than the market. Rather, it tries to identify risk factors with a strong economic rationale, and considerable empirical evidence in favor of a positive risk premium. Interestingly, recent research has identified fundamental characteristics that are similar to some of the descriptors of "quality," namely high profitability and low investment. For example, Asness (2014) notes that quality measures tend to "overlap with the profitability and investment factors." Both these factors have been found to be relevant in explaining the cross section of stock returns. Such factors would be straightforward alternatives to ad-hoc definitions of quality currently used in the asset management industry. The advantage of these factors is that they have been widely documented, extensively tested in the data independently by many academics and thoroughly explained in terms of the economic mechanisms underlying the associated premia.

In this article, we briefly review the high profitability and low investment factors and the economic rationale that lies behind their capacity to yield risk premia. Firstly, we summarize the empirical evidence of these two factors in explaining stock returns, and the rationale for a risk premium associated with these factors. Next, we construct well-diversified factor-tilted portfolios using long-term U.S. data for both factors and examine their risk and return characteristics. Lastly, we investigate if there are diversification benefits to combining the two factor indexes.

Is there a premium to high profitability and low investment stocks? Empirical evidence

Several papers in the empirical asset pricing literature aim to find factors that are priced or command a premium in the securities market. Although these findings are consistent with asset pricing theory, which allows for multiple sources of priced systematic risks (see e.g. Merton, 1973 and Ross, 1976), recent research argues that claims about premia attached to most of the factors are not significant (Harvey et al., 2014). Perhaps the most consensually accepted factors in academia (besides the market factor (Sharpe, 1964)) are size (Banz, 1981 and Fama and French, 1993), value (Fama and French, 1993) and momentum (Carhart, 1997). The acceptance of these factors is attributed to economic explanations and sufficiently robust evidence of the risk premium associated with them over a long history.

More recently, authors have documented profitability and investment as factors that explain a cross section of stock returns (see e.g. Fama and French, 2014; Novy-Marx, 2013, Cooper et al., 2008 and Titman et al., 2004). Although the authors differ on characteristics that can be used as a proxy for the profitability or investment factor, they present robust evidence that there is a premium associated with these factors. They also emphasize that the profitability or investment factors are not manifestations of other well-documented factors, such as the value factor. For example, Novy-Marx (2013) notes that profitability exhibits negative correlation with the value factor. Similarly, Cooper et al. (2008) note that the investment factor is a significant explanatory factor, even after controlling for factors such as value, size and momentum.

In the table below we report summary statistics of the five factors documented in Fama and French (2014). In panel A of the table, note that the monthly return on all five factors (market, size, value, profitability and investment) is positive over the last 50 years (July 1963-December 2013) and is statistically significant. Over this period, the average monthly return on the investment and the profitability factor is positive (0.17% and 0.22%) and statistically significant (at a 95% confidence interval), with t-statistics of 2.79 and 3.72.

In panel B, we report correlation between different factors over the last 50 years. Note that the profitability factor has negative correlation with the market (-0.13), size (-0.32) and investment factors (-0.19), whereas it has positive but low correlation with the value factor (0.04). The investment factor has negative correlation with the market (-0.43), size (-0.13) and profitability (-0.19) factors and positive correlation with the value factor (0.71). The low or negative correlation of the profitability and investment factors with other factors underlines the diversification benefit of combining these factors in a portfolio.

Profitability is usually defined by the Gross Profitability of the firm as the proxy variable. The outperformance of profitable over unprofitable companies has been documented in a recent paper by Novy-Marx (2013), who uses the ratio of gross profit (revenues minus cost of goods sold) to total assets as the measure of profitability. Cohen, Gompers and Vuolteenaho (2002) provide similar evidence showing that — when controlling for book-to-market — average returns tend to increase with profitability. Alternative definitions of profitability are, for example, the ratio of Operating Profit to Book Equity, i.e., Return-on-Equity (Fama and French, 2014). Gross profitability has the advantage of avoiding reliance on accounting manipulations, as gross profits are a very high-level measure of profits.

Investment is usually defined as the growth rate of total assets of the firm (Fama and French, 2014). Cooper et al. (2008) show that a firm's investment, characterized by the one-year total asset growth rate, determines its stock returns. In their analysis, low investment firms generate about 8% annual outperformance over high investment firms. A negative relation between investment and stock returns is also documented by Xing (2008), Lyandres, Sun, and Zhang (2008), and

EXHIBIT 1

Summary statistics of factors (Source: Fama and French, 2014) — Panel A of the table reports the average of monthly factor returns and their t-statistics. The market factor is the return on all sample stocks minus the one-month U.S. Treasury bill rate. The size, value, profitability and investment factors are created as returns on small minus large capitalization portfolios, high minus low book-to-market portfolios, high minus low operating profitability portfolios and low minus high asset growth portfolios, respectively. The value, profitability and investment factors are constructed after controlling for size. All the portfolios are value weighted. The period and sample for analysis is July 1963 to December 2013 and the firms are incorporated in the U.S. and listed on NYSE, AMEX or NASDAQ. Panel B reports correlation between the five factors. We refer readers to Fama and French (2014) for a detailed description of the construction of the five factors presented here.

Panel A: Summary Statistics

	Market	Size	Value	Profitability	Investment
Average monthly return (in %)	0.50	0.30	0.28	0.17	0.22
t-statistics	2.74	2.33	3.22	2.79	3.72

Panel B: Correlation Between Factors

	Market	Size	Value	Profitability	Investment
Market	1	0.30	-0.34	-0.13	-0.43
Size		1	-0.16	-0.32	-0.13
Value			1	0.04	0.71
Profitability				1	-0.19
Investment					1

Titman, Wei and Xie (2004). Ahroni, Grundy and Zeng (2013) show that even when controlling for profitability and book-to-market, there is a negative relationship between investment and returns.

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 that 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 superior to the Fama and French three-factor model in explaining cross sectional return patterns and profits to many well-known profitable equity trading strategies. In the following section, we present the economic rationale behind the investment and profitability factors.

Why should the investment and profitability premia persist? Economic rationale

Asset pricing theory suggests that a factor is positively rewarded if and only if it performs poorly in bad times but more than compensates in good times, resulting in positive excess return over the entire market cycle (i.e., when marginal utility is high (see e.g.. Cochrane, 2000)). While substantial empirical evidence is a necessary condition for considering that a reward for a certain factor exposure exists, it is not sufficient. In fact, a widely documented premium may disappear after it is being exploited by an increasing number of investors.

For the profitability and investment factors, several authors have provided an economic rationale for the existence of a risk premium. In fact, it is interesting to note that the premium for the profitability and investment factors can be explained directly using risk-based pricing, rather than using a behavioral explanation such as in the case of a premium associated with accruals (Sloan, 1996). Hou, Xue and Zhang (2014) argue that, since the investment and profitability factors should influence expected returns according to economic theory[1], using these factors "is less subject to the data-mining critique than the Fama-French model," i.e., the value and size factors. Two explanations suggesting a role for these factors are summarized below:

• Dividend discount model

Fama and French (2006) derive the relationship between book-to-market ratio, expected investment, expected profitability and expected stock returns from the dividend discount model, which models the market value of a stock as the present value of expected dividends. The dividend discount model, together with a set of accounting identities, lead to the following three predictions:

- Controlling for expected earnings and expected changes in book equity, high book-to-market implies high expected returns.
- Controlling for book-to-market and expected growth in book equity, more profitable firms (firms with high earnings relative to book equity) have higher expected returns.
- Controlling for book-to-market and profitability, firms with higher expected growth in book equity (high reinvestment of earnings) have low expected returns.

The second and the third predictions of the dividend discount model mentioned above justify the profitability and investment premium, i.e., high return on profitable firms compared to less profitable firms and high return on low investment firms compared to high investment firms.

• Production-based asset pricing

Hou, Xue and Zhang (2014) provide a more detailed economic model where profitability and investment effects arise in the cross section due to firms' rational investment policies (see also Liu, Whited and Zhang 2009).

Concerning the explanation of high returns for low investment firms, it is useful to recall that a firm's optimal investment decision satisfies the first order condition that the marginal benefit of investment discounted to the current date should equal the marginal cost of investment. Put differently, the investment return (defined as the ratio of the marginal benefit of investment to the marginal cost of investment) should equal the discount rate. This optimality condition means that the relationship between investment and expected returns is negative: if expected investment is low, expected returns are high. Intuitively (given expected cash flows), firms with high cost of capital (and thus high expected returns) will have difficulty finding many projects with positive net present value (NPV) and will thus not invest a lot.

Concerning the explanation of the link between high profitability and high expected stock returns, it should be noted that the optimality condition further implies a positive relationship between profitability and expected returns. High profitability (i.e., high expected cash flow relative to equity) at a given level of investment implies a high discount rate. Intuitively, if the discount rate were not high enough to offset the high profitability, the firm would face many investment opportunities with positive NPV and thus invest more by accepting less profitable investments.

Performance of smart factor indexes for low investment and high profitability tilts

We construct factor-tilted portfolios, called smart factor indexes, to extract the factor premia most efficiently using the two-step Smart Beta 2.0 process: one, explicitly selecting appropriate stocks for the desired beta and two, using a diversification-based weighting scheme (Amenc and Goltz, 2013). While various definitions of profitability exist in the literature, we use the Gross Profitability definition from Novy-Marx (2013) due to its parsimony and independence from accounting manipulations. For the low investment factor, we follow the factor definition used in the five-factor regression model developed by Fama and French (2014). The 50% of stocks with the lowest Asset Growth (past two-year growth rate of total assets) score are selected as Low Investment stocks and the 50% of stocks with the highest Gross Profitability (Gross Profit/Total Assets) score are selected as High Profitability. Diversified Multi-Strategy weighting is applied to each stock selection.[2] The reasons for selecting 50% of stocks, instead of a stronger tilt such as 30%, are threefold. Firstly, a broader stock universe provides more room for diversification. Also, it allows for another level of independent screening such as "highly liquid" stocks for investors who have liquidity constraints. Lastly, it ensures that there are sufficient stocks in the universe to accommodate constraints such as geographical neutral or sector neutral in a long-only portfolio, in case they are desired by investors.

Exhibit 2 summarizes the performance of portfolios tilted towards Low Investment and High Profitability stocks. The tilted cap-weighted portfolios beat the broad cap-weighted (CW) benchmark, which shows that both Low Investment and High Profitability factor tilts are rewarded in the long term. It is remarkable that the multi-strategy weighting scheme not only improves performance over tilted cap-weighted portfolios, but also does it with lower volatility. Consequently, both Low Investment and High Profitability smart factor indexes deliver Sharpe ratios in excess of 0.55, compared to a mere 0.41 for the broad CW benchmark.

Since smart factor indexes are constructed on half universes, their tracking error is substantial. However, information ratios of more than 0.72 imply that the indexes are quite well compensated for this deviation from the benchmark. Like any other risk factor, the low investment and high profitability factors also experience relative drawdown. To access the robustness of these smart-factor indexes, we compute an "outperformance probability," which is defined as the empirical frequency of outperforming the cap-weighted reference index over a given investment horizon. Both indexes achieve more than 80% outperformance probability for a three-year investment horizon, indicating high consistency.

Investibility of low investment and high profitability smart factor indexes

Turnover rules and liquidity rules are applied to smart factor indexes to overcome problems of high turnover and limited

EXHIBIT 2

All statistics are annualized. Yield on Secondary U.S. Treasury Bills (3M) is used as a proxy for the risk-free rate. The analysis is based on daily total return data from December 31, 1974 to December 31, 2014 (40 years). The Scientific Beta LTTR U.S. universe consists of the 500 largest U.S. stocks. Probability of outperformance is the probability of obtaining positive excess returns if one invests in the strategy for a period of three years (or one year) at any point during the history of the strategy. Rolling window of length three years (or one year) and a step size of one week are used. 95% TE is the 95th percentile of the one-year rolling tracking error computed using a one-week step size. Maximum relative drawdown is the maximum drawdown of the long/short index whose return is given by the fractional change in the ratio of strategy index to benchmark index.

Dec 1974 – Dec 2014 (40 Years)	Scientific Beta USA Long-Term Track Records				
	All Stocks	Low Investment		High Profitability	
	CW	CW	Multi-Strategy	CW	Multi-Strategy
Annual Returns	12.16%	13.96%	16.05%	12.63%	15.49%
Annual Volatility	17.12%	15.96%	15.34%	17.06%	15.95%
Sharpe Ratio	0.41	0.55	0.71	0.44	0.65
Maximum Drawdown	54.53%	53.38%	53.20%	52.29%	48.28%
Annual Relative Returns	-	1.80%	3.89%	0.47%	3.33%
Tracking Error	-	3.85%	5.44%	3.34%	4.39%
Information Ratio	-	0.47	0.72	0.14	0.76
Outperf. Prob. (1-Year)	-	61.54%	71.86%	51.23%	70.58%
Outperf. Prob. (3-Year)	-	75.21%	81.16%	58.59%	82.35%
95% Tracking Error	-	6.89%	10.06%	6.75%	7.58%
Max. Rel. Drawdown	-	26.47%	38.49%	20.27%	25.21%

[1] Although a unified economic theory (investment-based asset pricing theory) can be used to explain the premium to value, as well as to the profitability and investment factors, the stocks that are selected using high book-to-market (or value firms), high profitability and low investment criteria are not the same (for example, high profitable firms tend to have low book-to-market ratios and are growth firms).

[2] Diversified Multi-Strategy weighting is an equal-weighted combination of the following five weighting schemes: Maximum Deconcentration, Diversified Risk Weighted, Maximum Decorrelation, Efficient Minimum Volatility and Efficient Maximum Sharpe Ratio. For more information on the weighting scheme, please refer to the white paper "Scientific Beta Diversified Multi-Strategy Index" by Badaoui and Lodh (2013).

capacity, an issue usually cited in the case of factor investing. A conditional rebalancing approach is used such that it avoids unnecessary rebalancing unless a significant amount of new information has been received since the last index rebalancing, hence avoiding rebalancing due to noise. The capacity constraints allow us to manage the deviations from the cap-weighted reference index in terms of individual stock weights both at the trading and the holding levels.[3]

To foster more liquidity, investors have the option of making a highly liquid stock selection on top of the existing factor-tilted selection. These indexes are constructed on the 70% most liquid stocks among the selected stocks and are called high liquidity smart factor indexes. Exhibit 3 shows that the capacity of standard smart factor indexes is sufficiently high at $11.1 billion and $15.2 billion compared to $50.2 billion for the broad CW index. The "Highly Liquid" filter improves capacity drastically and has little impact on performance or turnover. Two levels of transaction costs are used: 20 basis points per 100% 1-W turnover and 100 basis points per 100% 1-W turnover.[4] The excess returns net of transaction costs are still quite significantly high.

Combining low investment and high profitability factor tilts

Many commercial indexes marketed under the umbrella of "quality" indexes do not make a distinction between the Low Investment and High Profitability factors. Instead, they use a composite of a wide range of scores. Most of them do not comply with either factor.[5] Exhibit 4 shows the benefit of a quarterly rebalanced equal-weighted combination of the two smart factor indexes and compares it with the stand-alone results of its component indexes, but also to various "quality" indexes from well-known index providers over a 10-year period.

It should be noted that competitors mix a systematic approach to stock picking (alpha) with criteria used to define beta. For example, scoring stocks by a combination of return on equity (ROE) score and earnings variability score could be a good criterion if the objective is stock picking. However, reward for systematic risk does not exist for a combination of scores, meaning that making a stock selection based on a composite score does not tilt the portfolio to either beta. It selects stocks that are ranked moderately in both scores and therefore do not necessarily represent either systematic risk. This approach is therefore confusing and does not capture all possible risk premia, an example being the absence of any variable that explicitly provides exposure to the investment factor.

The competing "quality" indexes use a quality score to weight the portfolio in a variety of ways, ranging from using the quality score to tilt market-cap portfolios (MSCI's approach), converting quality scores into active weights using a probability algorithm (Russell's approach) to weighting stocks in proportion to their quality scores (S&P's approach). Irrespective of the definition of quality, ignoring stock correlations in the weighting results in a less-diversified portfolio, which in turn results in inferior performance. This is the reason why both the Low Investment and High Profitability Multi-Strategy portfolios outperform the three competing indexes. The combination of high profitability and low investment factor indexes results in tracking error reduction, leading to an information ratio of 0.87, which is higher than or equal to the information ratio of either component. This suggests that combining the two factor tilts results in a diversification benefit, which naturally occurs with any set of separate factors that have low correlation with each other.

Compared to other commercially available indexes, the high profitability and low investment combination displays a higher excess return (2.76%) and similar or lower volatility, resulting in a higher Sharpe ratio (0.49) over the 10-year period under analysis. From a relative risk perspective as well, this index displays better risk-adjusted performance, as evidenced by its higher information ratio and outperformance probability for the 10-year sample period analyzed. •

CONCLUSION

Recent empirical studies document the role of two separate factors related to balance sheet characteristics: Low Investment and High Profitability. These factors rely on straightforward and parsimonious indicators, and can be expected to provide more robust performance benefits than ad-hoc stock picking indicators of "quality" used in the industry. In fact, using these factors, which are documented by independent research, avoids the risk of data-mining inherent in ad-hoc stock ranking methods. The performance of factor indexes aiming to capture the high profitability and low investment premium can be improved by the use of a diversification-based weighting scheme such as Diversified Multi-Strategy weighting. Further value can be added by allocating across these two factors to exploit the low correlation across factor returns. Such combinations of the smart factor indexes for high profitability and low investment have led to improved performance compared to various commercial indexes that are based on ad-hoc definitions of "quality."

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EXHIBIT 3

All statistics are annualized. The analysis is based on daily total return data from December 31, 1974 to December 31, 2014 (40 years). The Scientific Beta LTTR U.S. universe consists of the 500 largest U.S. stocks. The effective number of stocks (ENS) is defined as the reciprocal of the Herfindahl Index, which is defined as the sum of squared weights across portfolio constituents. Mean Capacity is the weighted average market capitalization of the index in $million. Reported turnover is one-way annualized. Net relative returns are the relative returns after accounting for transaction costs (One-way Turnover * 20 basis points (or 100 basis points)).

Dec 1974 – Dec 2014 (40 Years)	All Stocks CW	Scientific Beta USA Long-Term Track Records			
		Standard		Highly Liquid Selection	
		Low Investment	High Profitability	Low Investment	High Profitability
Effective Number of Stocks	117	190	201	117	124
Capacity ($million)	50,222	11,108	15,221	15,744	22,533
Annual 1-Way T.O.	2.68%	31.70%	22.21%	33.92%	24.08%
Information Ratio	-	0.72	0.76	0.67	0.64
Annual Relative Returns	-	3.89%	3.33%	3.29%	2.54%
Net Rel. Returns (20 bps)	-	3.83%	3.29%	3.22%	2.49%
Net Rel. Returns (100 bps)	-	3.58%	3.11%	2.95%	2.29%

EXHIBIT 4

All statistics are annualized. Yield on Secondary U.S. Treasury Bills (3M) is used as a proxy for the risk-free rate. The S&P 500 Index is used as the broad cap-weighted benchmark. The analysis is based on daily total return data from December 31, 2004 to December 31, 2014 (10 years). The EW customized index is an equal-weighted combination of the Scientific Beta USA Low Investment Multi-Strategy and Scientific Beta USA High Profitability Multi-Strategy indexes, rebalanced quarterly. The Scientific Beta USA universe consists of 500 stocks. Probability of outperformance is the probability of obtaining positive excess returns if one invests in the strategy for a period of three years at any point during the history of the strategy. Rolling window of length three years and a step size of one week are used.

Dec 2004 – Dec 2014 (10 Years)	S&P 500 Index	Scientific Beta USA			Competitors USA		
		Low Investment Multi-Strategy	High Profitability Multi-Strategy	Custom EW Combination	MSCI USA Quality Index	Russell 1000 Quality HEFI	S&P 500 High Quality Rankings
Annual Returns	7.65%	10.88%	10.59%	10.66%	9.05%	9.50%	7.79%
Annual Volatility	20.39%	18.81%	18.75%	18.92%	18.12%	19.34%	20.52%
Sharpe Ratio	0.30	0.50	0.49	0.49	0.42	0.42	0.31
Max Drawdown	55.25%	50.82%	47.58%	49.60%	44.03%	48.61%	57.68%
Annual Rel. Returns	-	3.23%	2.94%	2.76%	1.40%	1.85%	0.14%
Tracking Error	-	3.72%	4.45%	3.16%	4.65%	3.12%	4.81%
Information Ratio	-	0.87	0.66	0.87	0.30	0.59	0.03
Outperf. Prob. (3Y)	-	100.00%	91.80%	99.45%	83.33%	90.71%	62.84%

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[3] *The target turnover for smart factor indices is 30% 1-way annual. For more information on turnover and liquidity rules, please refer to the white paper "Overview of Diversification Strategies" by Gonzalez and Thabault (2013).*
[4] *The first case corresponds to the worst case observed historically for the large and mid-cap universe of our indices, while the second case assumes 80% reduction in market liquidity and a corresponding increase in transaction costs.*
[5] *The MSCI Quality Index uses ROE, Debt-to-Equity and Earnings Variability; the Russell Quality HEFI Index uses ROA, Debt-to-Equity and Earnings Variability; and the S&P 500 High Quality Ranking Index uses Growth and Stability of Earnings and Recorded Dividends to compute the Quality score of stocks.*

PORTFOLIO MANAGEMENT

Identifying Equity Factors with a Genuine Economic Rationale

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

Sivagaminathan Sivasubramanian
Quantitative Analyst
ERI Scientific Beta

Questioning the economic rationale: a key part of due diligence

Index providers and asset managers have been prolific at creating equity strategies that tilt towards various "factors." While early attempts at factor investing concentrated on the small cap and value factors, we have seen a proliferation of factors that are supposed to be captured by investment products, including momentum, carry, "quality" and earnings revisions, to name a few. Rather than accepting new factors based on the back-tested performance improvements they bring, investors may be well advised to assess the theoretical groundings, i.e., the economic rationale, underlying a factor.

Asset pricing theory postulates that multiple sources of systematic risk are priced in securities markets. In particular, both equilibrium models such as Merton's (1973) intertemporal capital asset pricing model and no arbitrage models such as Ross's (1976) Arbitrage Pricing Theory allow for the existence of multiple priced risk factors. This is in contrast to Sharpe's (1963) Capital Asset Pricing Model, which identified the market factor as the only rewarded risk factor. However, such models do not contain an explicit specification of what these factors are, having led some to qualify them as "fishing licenses" that allow researchers to come up with ever new data-mined factors, creating a whole "factor zoo." In order to avoid such factor fishing, which carries the risk of ending up with factors that matter a lot in the sample but do not persist, there should be fundamental economic reasons as to why a given factor should be rewarded in the long term. Thus, a key requirement for investors to accept factors as relevant in their investment process is related to the presence of a clear economic intuition as to why the exposure to this factor constitutes a systematic risk that requires a reward and is likely to continue producing a positive risk premium (see Ang, 2013, and Cochrane, 2000). This article reviews the rationale for some of the widely used factors.

Evolution of multi factor asset pricing models

Empirical research has come up with a large variety of factors that explain differences in stock returns beyond what different exposure to the market factor can explain. The literature documents that such additional factors have led to significant risk premia in typical samples of data from U.S. and international equity markets.[6] Harvey, Liu and Zhu (2013) report that empirical literature has identified more than 300 published factors that impact the cross section of expected stock returns. But not all of these factors present a sound economic rationale, or more precisely, a well-accepted risk-based explanation for their apparent risk premiums.

In this, we focus on six the of most popular risk factors that indeed satisfy this condition and have therefore attracted immense attention in both academic and practitioner worlds alike — size, value, momentum, low risk, profitability and investment. The table below provides an overview of the main factors used in common multi-factor models of expected returns and the references to seminal work providing empirical evidence. It is interesting to note that these factors have been found to explain expected returns across stocks not only in U.S. markets, but also in international equity markets, and — in many cases — even in other asset classes, including fixed income, currencies and commodities.

EXHIBIT 1

Examples of factor risk premium reported in the literature

Factor	Time Period	Average Premium	T-statistic	Source
Market	1926-2008	7.72% (annual)	3.47	Ang et al. (2009)
Size	1926-2008	2.28% (annual)	1.62	Ang et al. (2009)
Value	1926-2008	6.87% (annual)	3.27	Ang et al. (2009)
Momentum	1926-2008	9.34% (annual)	5.71	Ang et al. (2009)
High Profitability	1963-2013	0.17% (monthly)	2.79	Fama and French (2014)
Low Investment	1963-2013	0.22% (monthly)	3.72	Fama and French (2014)

EXHIBIT 2

Empirical Evidence for Selected Factor Premia: Key References

	Factor Definition	Within US Equities	International Equities	Other Asset Classes
Value	Stocks with high book-to-market vs. stocks with low book-to-market	Basu (1977) Rosenberg, Reid, Lahnstein (1985) Fama and French (1993)	Fama and French (2012)	Asness, Moskowitz, Pedersen (2013)
Momentum	Stocks with high returns over the past 12 months omitting the last month vs. stocks with low returns	Jegadeesh and Titman (1993), Carhart (1997)	Rouwenhorst (1998)	Asness, Moskowitz, Pedersen (2013)
Low Risk	Stocks with low risk (beta, volatility or idiosyncratic volatility) vs. stocks with high risk	Ang, Hodrick, Xing, Zhang (2006), Frazzini and Pedersen (2014)	Ang, Hodrick, Xing, Zhang (2009), Frazzini and Pedersen (2014)	Frazzini and Pedersen (2014)
Size	Stocks with low market cap vs. stocks with high market cap	Banz (1981) Fama and French (1993)	Heston, Wessels, Rouwenhorst (1999) Fama and French (2012)	N.A.
Profitability	Stocks of firms with high profitability (e.g. return on equity) have high returns	Novy Marx (2013), Hou, Zhang and Xue (2014), Fama and French (2014)	Ammann, Odoni, Oesch (2012)	N.A.
Investment	Stocks of firms with low investment (e.g. change in book-value) have high returns	Cooper, Gulen, and Schill (2008) Hou, Zhang and Xue (2014), Fama and French (2014)	Ammann, Odoni, Oesch (2012) Watanabe, Xu, Yao, Yu (2013)	N.A.

[6] *These effects are often referred to as "anomalies" in the academic literature as they contradict the CAPM prediction that the cross section of expected returns only depends on stocks' market betas and should be void of any other patterns. However, when using a more general theoretical framework such as the intertemporal CAPM or Arbitrage Pricing Theory, there is no reason to qualify such patterns as anomalies.*

[2] *Institutional elements such as those governing the surplus sharing rule, the tax rate and bankruptcy costs will also have an impact on the numerical results.*

Fama and French (1993) highlighted two important factors that explain stock returns in addition to the market factor. They show that stock returns are related to exposure to the value factor (the return difference of high vs. low book-to-market-ratio stocks) and exposure to the size factor (return difference of stocks from small versus large companies as measured by market capitalization). Their three-factor model is a parsimonious way of capturing a range of seemingly different return patterns that have been highlighted in the empirical literature. Carhart (1997) extended the Fama and French three-factor model to where the additional factor is momentum, which captures return differences between past winner and past loser stocks (measured over an intermediate horizon of about one year). This factor was added to take the pattern revealed by Jegadeesh and Titman (1993) into account.

While the Fama and French (1993) and Carhart (1997) models have remained the workhorses of multi-factor modeling and its applications for more than a decade (see also Fama and French, 2012, or Hou, Karolyi and Kho, 2011), recent research suggests that yet more factors may be needed to capture empirical return patterns. Recently, Fama and French (2014) examined an augmented version of the three-factor Fama and French model (FF 1993) that adds profitability and investment factors to the market, size and B/M factors of the FF model. The authors find that the model provides an acceptable description of average returns on portfolios formed on size and one or two of B/M, operating profitability and investment. Asness et al. (2013) argue that the momentum factor adds explanatory power to the Fama and French five-factor model, and Fama and French (2014) argue that their model is likely to be unable to capture returns to low-risk equity portfolios, such as low beta or low volatility portfolios. These considerations lead us to discuss six main risk factors, which are empirically documented and widely accepted. Exhibit 1 shows the historical factor premiums of some of the factors.

Exhibit 2 summarizes the various factor definitions and their corresponding literature survey references in various asset classes.

Rationale behind equity risk factors

In the previous section we discussed different empirical evidence of the presence of various factor premia. In this section, we analyze why such factor premia exist. The existence of factor premia can be explained in two different ways — a risk-based explanation and a behavioral-bias explanation. The risk-based explanation premises that the risk premium is compensation to investors who are willing to take additional risk by being exposed to a particular factor. The behavioral explanation conceives that the factor premia exist because investors make systematic errors due to behavioral biases such as overreaction or under-reaction to news on a stock.

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, that 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. It is for this reason, in addition to space constraints, that we do not explore behavioral explanations in detail in the text, and we refer to Exhibit 3 for a brief list of behavioral explanations of each factor. In an efficient market with rational investors, systematic differences in expected returns should be due to differences in risk. Kogan and Tian (2012) argue that to determine meaningful factors, "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." This point is best illustrated by the example of the equity risk

EXHIBIT 3

Economic Explanations for Selected Factor Premia: Overview

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

premium. Given the wide fluctuation in equity returns, the equity risk premium can be statistically indistinguishable from zero even for relatively long sample periods. However, one may reasonably expect that stocks have a higher reward than bonds because investors are reluctant to hold too much equity due to its risks.

Value

Zhang (2005) provides a rationale for the value premium based on costly reversibility of investments. The stock price of value firms is mainly made up of tangible assets, which are hard to reduce, while the stock price of growth firms is mainly driven by growth options. Therefore, value firms are much more affected by bad times and the value premium can thus be interpreted as compensation for the risk of suffering from losses in bad times. Lakonishok, Shleifer and Vishny (1994) argue that value premium exists because of the psychological tendency of investors to extrapolate recent developments into the future and to ignore evidence that is contrary to the extrapolation.

Momentum

Momentum stocks are exposed to macroeconomic risk. In particular, Liu and Zhang (2008) provide empirical evidence that past winners have temporarily higher loadings on the growth rate of industrial production and are therefore more exposed to shocks to expected growth. Behavioral explanations for momentum profits focus on the short-term overreaction of investors. Daniel et al. (1998) show that two cognitive biases, overconfidence and self-attribution, can generate momentum effects.

Low Risk

Frazzini and Pedersen (2014) provide a model in which liquidity-constrained investors are able to invest in leveraged positions of low-beta assets but are forced to liquidate these assets in bad times when their liquidity constraints mean that they can no longer sustain the leverage. Therefore, low-risk assets are exposed to a risk of liquidity shocks and investors are compensated for this risk when holding low-beta assets. Behavioral explanations for the low-risk premium argue that high-risk stocks tend to have low returns because irrational investors bid up prices beyond their rational value.

Size

Small stocks tend to have lower profitability (in terms of return on equity) and greater uncertainty of earnings (see Fama and French, 1995), even when adjusting for book-to-market effects. Therefore, such stocks are more sensitive to economic shocks, such as recessions. It has also been argued that stocks of small firms are less liquid and expected returns of smaller firms have to be large in order to compensate for their low liquidity (Amihud and Mendelson, 1986). It has also been argued that smaller stocks have higher downside risk (Chan, Chen and Hsieh, 1985).

Profitability and Investment

Using a dividend discount model, which models the market value of a stock as the present value of expected dividends, Fama and French (2006) show that, controlling for book-to-market and expected growth in book equity, more profitable firms (firms with high earnings relative to book equity) have higher expected return. Also, controlling for book-to-market and profitability, firms with higher expected growth in book equity (high reinvestment of earnings) have lower expected returns.

Hou, Xue and Zhang (2012) provide a more detailed economic model where profitability and investment effects arise in the cross section due to firms' rational investment policies (see also Liu, Whited and Zhang, 2009). In particular, a firm's investment decision satisfies the first order condition that the marginal benefit of investment discounted to the current date should equal the marginal cost of investment. Put differently, the investment return (defined as the ratio of the marginal benefit of investment to the marginal cost of investment) should equal the discount rate. This optimality condition means that the relation of investment and expected returns is negative. Intuitively (given expected cash flows), firms with high cost of capital (and thus high expected returns) will have difficulty finding many projects with positive net present value (NPV) and thus not invest a lot. The optimality condition further implies a positive relationship between profitability and expected returns.

To conclude, several risk factors have been empirically evidenced both in the U.S. and on international equity markets, and several economic explanations have been proposed in the literature. To be sure, there is uncertainty around these explanations, and the debate over why a given factor may carry a premium is ongoing for all the factors mentioned. However, having a convincing explanation should be a key requirement for investors when they decide to gain exposure to a given factor, as a theoretical justification of an observed effect provides some safeguard against data-mining.

We also note that the economic rationale is important because the measurement of risk premia is analyzed based on an estimate of mean returns, which are notoriously hard to estimate reliably (see Merton, 1980) and thus naturally gives rise to debate in the literature. Several papers have discussed whether common factor premia such as small cap, momentum and value really exist in the data (see Fama and French, 2012[7], McLean and Pontiff, 2013[8] and Lesmond, Schill and Zhou, 2004[9]). The analysis of an economic rationale goes beyond such difficulties. •

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[7] Fama and French (2012) analyse how the four-factor model in Carhart (1997) performs in explaining the cross section of stock returns in developed equity markets around the world. They analyse stocks for four regions (North America, Europe, Japan and Asia Pacific excluding Japan). They find that both the value and the momentum effect are more pronounced in small cap stocks, and especially micro-cap stocks, than in large cap stocks. In particular, neither the large cap momentum factor nor the large cap value factor have returns that are significantly different from zero at conventional levels of significance, and the difference in factor returns within small cap stocks compared to within large cap stocks is significant for both the value and momentum factor.

[8] The authors find evidence that the average return predictability of the characteristics decays by 35% post publication and this is statistically significant.

[9] Lesmond, Schilb and Zhou (2004) find that relative strength strategies (or momentum strategies) require high turnover and thus heavy trading among costly stocks. The authors provide evidence that high trading costs are associated with stocks that generate momentum returns which imply that the trading profit opportunities observed in stocks vanish.

PORTFOLIO MANAGEMENT

Smart Beta Performance is not "Monkey Business"

Noël Amenc
Professor of Finance, EDHEC Business School; Director EDHEC-Risk Institute; and CEO, ERI Scientific Beta

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

Ashish Lodh
Senior Quantitative Analyst
ERI Scientific Beta

Questioning "monkey portfolio" arguments

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

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

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

In this article, we report results to a series of straightforward tests of these claims. In order to test the various claims, we distinguish the two main claims made by monkey portfolio proponents:

i) all smart betas have unavoidable value and small cap tilts resulting in performance that is similar across strategies
ii) smart beta strategies are as good as inverse or "upside-down" strategies

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

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

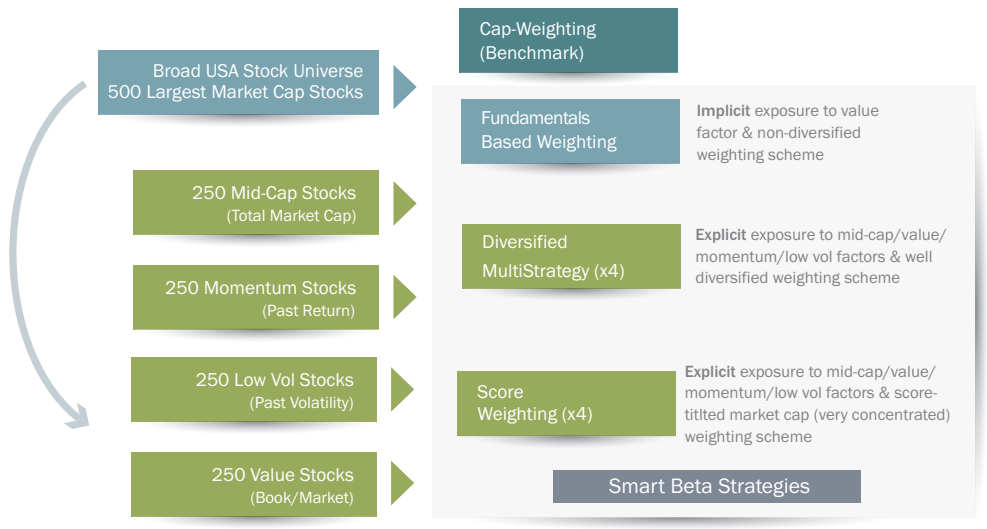
Our set of smart beta strategies

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

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

EXHIBIT 1

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



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

Among possible strategies, we included a broad set of smart beta strategies in our tests. First, we include the popular fundamentals-weighted portfolio strategy based on broad universe — a Smart Beta 1.0-type strategy. Given that many monkey portfolio proponents are also promoters of fundamentals-weighted indexes, it is interesting to first check whether their general claims apply to the type of smart beta strategy they promote. Second, we include a variety of Smart Beta 2.0 strategies that seek explicit exposure to a given risk factor by selecting stocks with desired factor exposures, or by using a weighting that favors stocks with certain characteristics, or both. Such smart beta strategies are being offered as "factor indexes" by most major index providers. Exhibit 1 provides an overview of the nine smart beta strategies we have constructed for our tests. In addition to the broad fundamentals-weighted strategy[10], we construct factor-tilted smart beta strategies that select half the stocks in the universe to obtain the desired factor tilt and then use a diversified multi-strategy weighting scheme across index constituents[11]. In addition, we test factor-tilted smart beta strategies that use the factor scores to determine constituent weights[12] among selected stocks. Such score-weighting is employed by factor indexes from a variety of major providers. The factor tilts we consider relate to the most widely used and documented factor tilts, namely low volatility, momentum, size and value. The factor indexes are rebalanced quarterly. All strategies are applied to the US large-cap stock universe (500 stocks) over a period of 40 years (December 31, 1973 to December 31, 2013). To avoid any hindsight bias, all parameters used in selecting and weighting the stocks are based on data observed prior to each respective rebalancing date.

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

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

[10] A composite fundamental weight is obtained, which is the average across four weights, each based on Current Book Value, Trailing 5-year Cash Flow, Trailing 5-year Dividend and Trailing 5-year Sales. The portfolio is rebalanced yearly on the third Friday in March.

[11] Diversified Multi-Strategy weighting is an equal weighted combination of the following five weighting schemes - Maximum Deconcentration Diversified Risk Weighted, Maximum Decorrelation, Efficient Minimum Volatility and Efficient Maximum Sharpe Ratio.

[12] Score weighting is done by weighting the stocks in proportion to their market-cap times the s-score of the respective factor. $W_i = \frac{S_i \cdot MC_i}{\sum_{k=1}^{N} S_k \cdot MC_k}$

In order to assess what the role of such additional factors is relative to the value and size factor, we perform regressions using a five-factor model that uses the Betting-Against-Beta (BAB) factor from Frazzini and Pedersen (2014)[13] in addition to the four factors in Carhart (1997), namely the market, value, size and momentum factors.

Exhibit 2 shows that exposures of most of the smart beta strategies we test to factors such as momentum (MOM) and BAB are both large in magnitude and statistically significant. Compared to the value and size factors, these additional factors are equally important in explaining the variation in portfolio returns. As expected, the low-volatility-tilted portfolios have a pronounced exposure (with coefficients of around 0.12) to the BAB factor and a low exposure of around 0.83 to 0.85 to the market factor. The Momentum Diversified Multi-Strategy portfolio has a MOM beta of 0.18 while Momentum Score Weighted has an even higher MOM beta of 0.39. Clearly, given these exposures, it would not make sense to claim that the returns to these low-volatility and momentum-tilted portfolios are fully explained by their size and value exposure.

Exhibit 3 shows the breakdown of excess returns of these strategies into components derived from factors and the unexplained part. The fundamentals-weighted portfolio does in fact rely mostly on exposure to the HML factor, but this is not true for all strategies. The low volatility and momentum-tilted portfolios, irrespective of the weighting scheme, derive a large portion of their performance from their exposure to BAB and MOM factors, respectively.

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

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

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

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

EXHIBIT 2

Five-Factor Regression

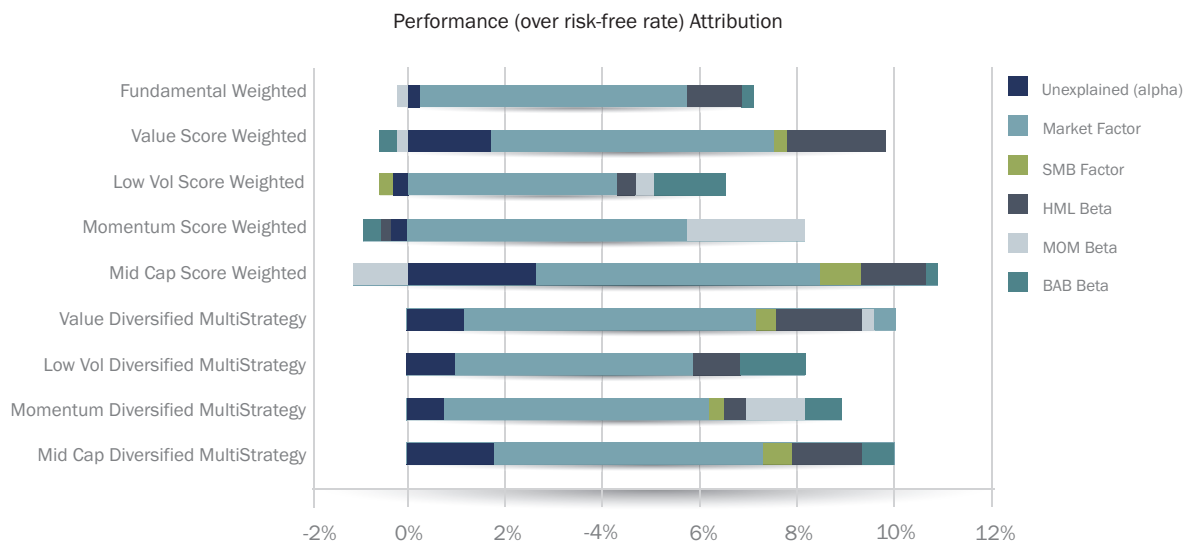
The market factor is the excess returns of the S&P 500 index over the risk-free rate. The yield on Secondary U.S. Treasury Bills (3M) is used as a proxy for the risk-free rate. Size, Value and Momentum factors are obtained from Kenneth French's data library. The Betting-Against-Beta (BAB) factor is obtained from Andrea Frazzini's data library. The Newey-West (1987) estimator is used to correct for autocorrelation and betas significant at the 95% confidence level are shown in boldface. Daily total returns from December 31, 1973 to December 31, 2013 are used for the analysis. Source: www.scientificbeta.com.

Weighting Scheme	Diversified Multi-Strategy				Score Weighting				Fundamental
Stock Selection	Mid Cap	Momentum	Low Vol	Value	Mid Cap	Momentum	Low Vol	Value	All
Annual Alpha	1.13%	0.24%	0.60%	0.76%	**2.35%**	-0.58%	-0.50%	1.26%	-0.01%
Market Beta	**1.00**	**0.98**	**0.85**	**1.00**	**1.06**	**1.04**	**0.83**	**1.07**	**0.99**
SMB Beta	**0.42**	**0.20**	**0.04**	**0.26**	**0.47**	**0.06**	**-0.20**	**0.13**	0.01
HML Beta	**0.33**	**0.12**	**0.24**	**0.45**	**0.34**	**-0.05**	**0.10**	**0.54**	**0.31**
MOM Beta	-0.01	**0.18**	0.00	**0.03**	**-0.18**	**0.39**	**0.06**	**-0.03**	**-0.03**
BAB Beta	**0.06**	**0.06**	**0.12**	**0.05**	0.01	**-0.03**	**0.12**	**-0.05**	**0.02**
R-squared	91.6%	95.1%	91.6%	94.7%	91.9%	96.6%	92.4%	95.4%	98.2%

EXHIBIT 3

Five-Factor Performance

The market factor is the excess returns of the S&P 500 index over the risk-free rate. The yield on Secondary U.S. Treasury Bills (3M) is used as a proxy for the risk-free rate. The Size, Value and Momentum factors are obtained from Kenneth French's data library. The Betting-Against-Beta (BAB) factor is obtained from Andrea Frazzini's data library. All statistics are annualized and daily total returns from December 31, 1973 to December 31, 2013 are used for the analysis. Source: www.scientificbeta.com.



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

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

First of all, we should note that whether or not a strategy behaves differently from its inverse will depend heavily on the type of strategy that one tests. Let us take the example of an

[13] *Rank-weighted portfolios that are long the 50% low market beta stocks and short the 50% high market beta stocks are constructed. Betas are estimated using the shrinkage method of Vasicek (1973) for long and short legs separately. Both long and short portfolios are rescaled to have a beta of one at portfolio formation.*

equal-weighted (also known as 1/N) strategy, which is the simplest form of smart beta strategy. If one inverts its weights using the methodology in Arnott et al. (2013), one would arrive at the original portfolio (i.e., the inverse of the 1/N portfolio is the portfolio itself). Therefore both this smart beta strategy and its inverse outperform the CW benchmark. Similarly, by using portfolios which are constrained to correspond to some optimization objective while keeping a close distance to equal-weighted portfolios, one would bias the results in favor of the claim that inverse strategies have as much merit as the original strategies.

We use the nine strategies introduced above to assess the claim that the performance of smart beta strategies remains the same or increases if their weights are inverted. To analyze this effect, we construct the inverse or upside-down portfolios for each smart beta strategy in a manner similar to that of Arnott et al. (2013).[14]

Exhibit 4 shows a basic performance comparison of portfolios and their upside-down counterparts. With the exception of the fundamentals-weighted portfolio, all smart beta portfolios outperform their upside-down counterparts and they do so mostly by large margins. Value Diversified Multi-Strategy posts 4.09% returns over its inverse and the Momentum Score Weighted portfolio beats its inverse by 4.81% annually. This is because the inverse of a factor-tilted portfolio tilts negatively towards the rewarded factor and hence does not benefit from risk premia. Therefore, investment beliefs in the form of explicit factor tilts do indeed play an important role in determining performance of an investment strategy.

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

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

EXHIBIT 4

Performance and Risk Analysis of Upside-Down Strategies

The probability of outperformance is the probability of obtaining positive excess returns from investing in the strategy for a period of three years at any point during the history of the strategy. All statistics are annualized and daily total returns from December 31, 1973 to December 31, 2013 are used for the analysis. The S&P 500 index is used as the cap-weighted benchmark. The yield on Secondary U.S. Treasury Bills (3M) is used as a proxy for the risk-free rate. Source: www.scientificbeta.com.

Stock Selection	Weighting Scheme	Ann. Returns	Ann. Volatility	Sharpe Ratio	Ann Rel. Returns	Ann Trk. Error	Information Ratio	Outperf. prob (3Y)
Mid Cap	Div Multi-Strategy	15.67%	16.69%	0.62	4.72%	6.65%	0.71	74.7%
Large Cap	Upside-Down	12.11%	18.10%	0.38	1.16%	3.45%	0.34	63.8%
High Momentum	Div Multi-Strategy	14.57%	16.26%	0.57	3.62%	4.83%	0.75	84.5%
Low Momentum	Upside Down	12.53%	19.68%	0.37	1.58%	7.99%	0.20	59.3%
Low Volatility	Div Multi-Strategy	13.90%	14.34%	0.60	2.95%	6.13%	0.48	76.5%
High Volatility	Upside-Down	13.06%	21.31%	0.36	2.11%	7.77%	0.27	61.7%
Value	Div Multi-Strategy	15.70%	16.51%	0.63	4.75%	5.74%	0.83	78.8%
Growth	Upside-Down	11.61%	18.47%	0.34	0.66%	4.82%	0.14	49.2%
Mid Cap	Mid Cap Score Weighting	15.40%	18.34%	0.55	4.45%	7.40%	0.60	68.9%
Large Cap	Upside-Down	9.91%	17.80%	0.26	-1.04%	2.72%	-0.38	28.3%
High Momentum	High Momentum Score Weighting	12.91%	18.35%	0.41	1.96%	5.69%	0.34	79.9%
Low Momentum	Upside-Down	8.10%	21.15%	0.13	-2.85%	9.04%	-0.32	21.0%
Low Volatility	Low Volatility Score Weighting	11.49%	14.75%	0.42	0.54%	5.91%	0.09	62.0%
High Volatility	Upside-Down	9.06%	26.07%	0.14	-1.89%	12.42%	-0.15	40.4%
Value	Value Score Weighting	14.89%	18.52%	0.52	3.94%	5.94%	0.66	77.6%
Growth	Upside-Down	8.88%	18.06%	0.20	-2.07%	4.10%	-0.51	31.9%
All Stocks	Fundamental Weighted	12.51%	16.84%	0.43	1.56%	3.58%	0.44	69.5%
All Stocks	Upside-Down	12.62%	17.21%	0.42	1.67%	4.08%	0.41	67.0%

Assessing smart beta strategies is not monkey business

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

Our findings of important differences across various smart beta strategies imply that care must be taken not to fall into the trap of oversimplification and overgeneralization. The differences in factor exposures across smart beta strategies imply that using a particular set of indexes corresponds to particular factor selection and factor allocation decisions. Moreover, the different factor tilts play an important role in shaping the risk-return profile of smart beta strategies. Factor-tilted smart beta strategies perform due to large positive exposure to their respective factors, while their inverted counterparts underperform the originals due to less pronounced or negative exposure to the same factors. When considering the adoption of smart beta strategies, investors should carefully consider which set of factor exposures is best aligned with their investment beliefs and objectives. Selecting among smart beta strategies is not monkey business after all.

To conclude this article, we are convinced that it is in the interest of both investors and providers to try to distance oneself from a research approach that is overly guided by commercial concerns. While recent years have seen the development of new offerings and concepts that ultimately lead to better benchmarks in terms of absolute (Sharpe ratio) and relative (Information ratio) performance, it is a shame that this progress is denied by research that lacks rigor and aims to lead one to believe that since everything is identical, it is better to choose first-generation smart beta offerings, which have longer live track records and more commercial references. •

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

Let the weight of a smart beta strategy be given by W.

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

The upside-down portfolio weights are given by the following expression:

$$W_{UD} = \left\{\frac{w_{max} - w_1}{n.w_{max} - 1}, \frac{w_{max} - w_2}{n.w_{max} - 1}, \ldots\ldots \frac{w_{max} - w_n}{n.w_{max} - 1}\right.$$

Similarly, the upside-down version of the Mid-Cap Score-Weighted portfolio is the portfolio obtained by inverting the size scores of large cap stocks such that larger stocks have higher s-scores.

$$S_i' = \max(S_1, S_2, \ldots\ldots S_n) - S_i$$

These scores are then used to tilt the market cap weighted portfolio of large cap stocks as follows:

$$W_i = \frac{S_i' . MC_i}{\sum_{k=1}^{N} S_k . MC_k}$$

PORTFOLIO MANAGEMENT

Investment Professionals' Views on Alternative Equity Beta Strategies

Véronique Le Sourd,
Senior Research Engineer
EDHEC-Risk Institute

Alternative equity beta investing has received increasing attention in the industry recently. Though products in this segment currently represent only a fraction of overall assets, there has been tremendous growth recently in terms of both assets under management and new product development. In this context, EDHEC-Risk recently carried out a survey[15] among a representative sample of investment professionals to identify their views and uses of alternative equity beta. The present article displays the main results of this survey.

While "smart beta" is used broadly in the industry as a catch-all phrase for new indexation approaches that deviate from broad cap-weighted market indexes, a recent trend is the appearance of factor indexes that specifically target certain rewarded risk factors. In fact, the early generation of smart beta approaches (Smart Beta 1.0) aimed either at improving portfolio diversification relative to heavily concentrated cap-weighted indexes (examples of such approaches are equal-weighting or equal-risk contribution, to name but two) or at capturing additional factor premia available in equity markets (such as value indexes or fundamentally-weighted indexes, which aim to capture the value premium).

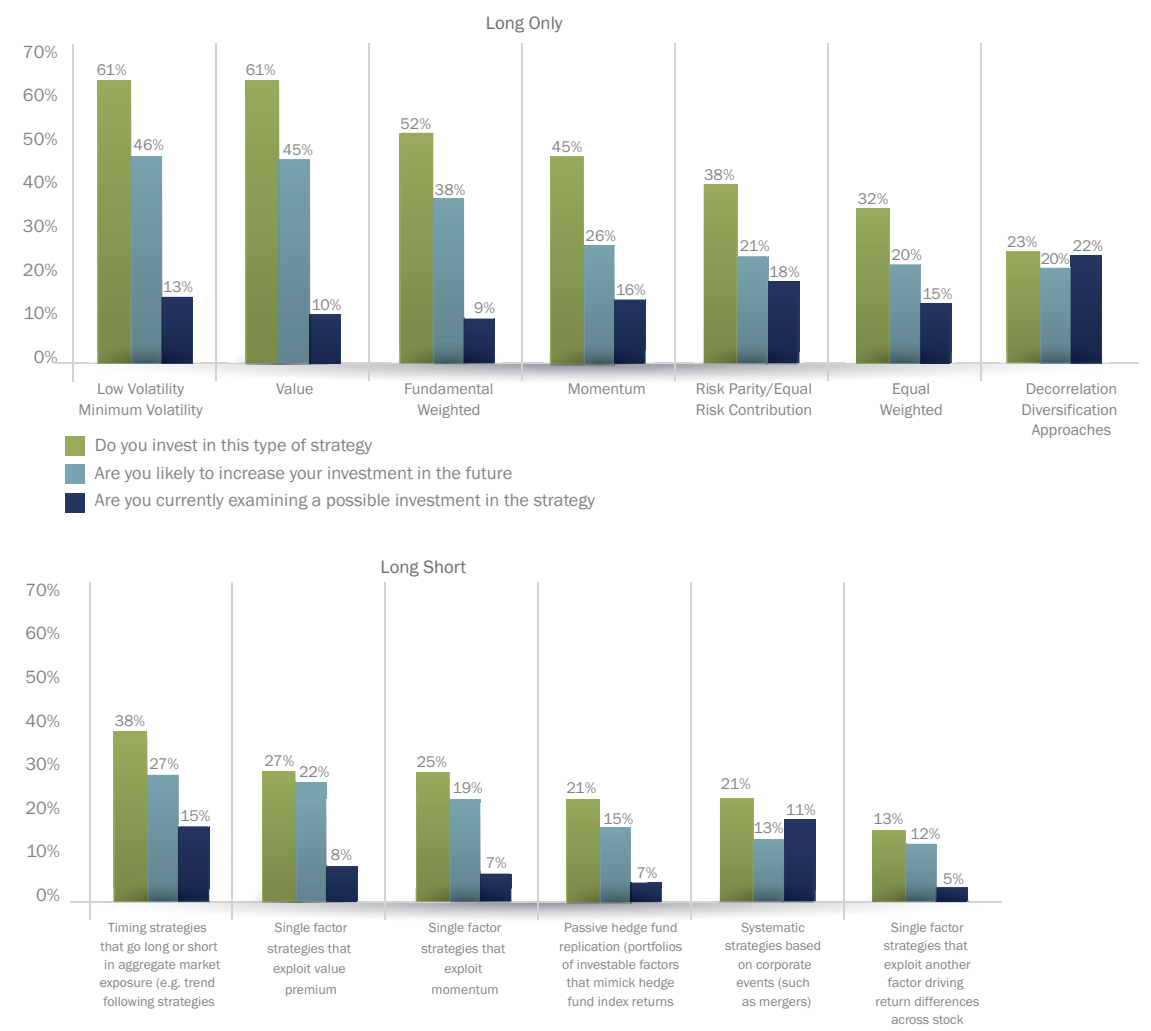
A potential shortcoming of focusing only on either improving diversification or capturing factor exposures is that the outcome, though improving upon broad cap-weighted indexes, may be far from optimal. In fact, diversification-based weighting schemes will necessarily result in implicit exposure to certain factors, thus carrying the risk of unintended consequences for investors who may not be aware of the implicit factor exposures. Factor-tilted strategies, which do not consider a diversification-based objective, on the other hand, may result in highly concentrated portfolios to achieve their factor tilts. More recently, investors have started to combine both factor tilts and diversification-based weighting schemes to produce well-diversified portfolios with well-defined factor tilts, using a flexible approach referred to as Smart Beta 2.0. This approach, in particular, allows the design of factor-tilted indexes (by using a stock selection based on factor-related characteristics of stocks) that are also well diversified (through the use of a diversification-based weighting scheme among the stocks with the desired factor exposures). Such an approach is also referred to as "smart factor investing," as it combines both the smart weighting scheme and the explicit factor tilt (see Amenc et al., 2014a). More recently, investors are increasingly turning their attention to allocation decisions across such factor investing strategies to generate additional value-added (see Amenc et al., 2014b).

Investment practices in alternative equity beta strategies are currently evolving at a fast pace, in line with an increasing variety of product offerings, and thus our survey was not aimed at providing a definitive account of practices in this area. However, with offerings and communication by providers increasing, the discussion of such strategies rarely provides a buy-side perspective. Our survey aims to fill this gap and provide the investors' perspective on such strategies. In our survey, we prefer the term "alternative equity beta" to refer to such strategies. The objective of our survey was to gain insights into investor perceptions relating to such advanced beta equity strategies, but also into the current uses they make of such strategies. We cover both long-only strategies and long/short strategies, but focus specifically on equity investments, and deliberately omit questions concerning alternative beta strategies in other asset classes. We asked respondents about their current use, familiarity, satisfaction and future plans with alternative beta strategies. Moreover, we gathered information on the due diligence process and the quality criteria that investors use to evaluate such strategies and assess their suitability for their own investment context. Before turning to some key results from our survey, we briefly introduce the methodology below.

EXHIBIT 1

Concerning your own investment in these types of strategies, please indicate for each of the following strategies your current status

For each of the strategies, this exhibit indicates the percentage of respondents that already invest in it, together with the percentage of respondents that are likely to increase their investment in the future. It also shows the percentage of respondents that do not invest in the strategy at the present time, but are considering a possible investment in the future.



Methodology and data

The survey allowed us to collect the opinions of 128 respondents, largely representative of alternative equity beta users. The survey covers different parts of the world; however, European respondents were predominant as they represent two-thirds of the sample, while 16% of respondents were from North America and 17% from other parts of the world, including Asia Pacific, the Middle East, Africa and Latin America. The respondents to the survey were mainly asset managers (64%) and institutional investors (20%). The majority of respondents were also key investment decision makers, including board members and CEOs (12%), CIOs, CROs, heads of asset allocation or heads of portfolio management (31%), and portfolio or fund managers (27%). Respondents were mainly from large firms having over €10 billion in asset under management (51%) or medium-sized companies with assets under management of between €100 million and €10 billion (39%).

Use of alternative equity beta and satisfaction rates

From this survey, it appears that the main argument for respondents to use alternative equity beta is to gain exposure

[15] Amenc, N., S. Badaoui, F. Goltz, V. Le Sourd, A. Lodh. 2015. Alternative Equity Beta Investing: A Survey. EDHEC-Risk Publication produced with the support of Newedge. The survey was conducted in 2014.

to rewarded risk factors, as well as to improve diversification relative to cap-weighted indexes[16], two arguments that are in accordance with the main criticisms of cap-weighted indexes. Respondents also declare that they are strongly motivated by the potential of alternative equity beta strategies to provide lower risk and higher returns than cap-weighted indexes, as well as by the transparency and low costs[17] of these strategies.

Respondents appear to be more familiar with long-only strategies than with long/short strategies. Consequently, the highest rates of investment, as well as the potential for increasing the investment in the future, are to be found among long-only strategies (see Exhibit 1). 61% of respondents invest in low volatility and value strategies, and 52% of respondents invest in fundamentals-weighted strategies, which were the strategies respondents indicate they were most familiar with. However, only 31% of respondents invest in the equal-weighted strategy, a naive strategy, though they are very familiar with it. The de-correlation approach appears to have potential for development in the future. While only 23% of respondents already invest in this type of strategy, 20% declare that they are likely to increase their investment in the strategy in the future, while another 22% are currently examining a possible investment in the strategy.

When asked to give their opinion about the current offering for the smart beta strategies they declare that they invest in, respondents credit all strategies, on average, with a positive rate of satisfaction (see Exhibit 2). However, higher satisfaction rates were obtained for long-only strategies, with the best score for the value strategy. In addition, long-only strategies respondents were the most familiar with received the highest rates of satisfaction, while the correlation between familiarity and satisfaction is not to be found among long-short strategies. For example, timing strategies were the ones respondents were the most familiar with, but the rate of satisfaction is one of the lowest among long/short strategies.

Challenges in evaluating and implementing alternative beta strategies

When they want to invest in alternative equity beta strategies, investors face different challenges that prevent them from investing more in alternative equity beta strategies. Not surprisingly, in view of the previous results, investors have better knowledge of evaluating and implementing long-only strategies than long/short strategies (see Exhibit 3). This relative lack of familiarity with long/short strategies is reflected in many additional and detailed results in our survey. Overall, it appears that investors feel that long/short strategies are too difficult to implement, and do not have extensive knowledge of these strategies or practical experience with investing in them. This is a notable difference with respect to long-only strategies, which are more widely used, and better understood by respondents, according to their own account.

However, even for long-only strategies, it appears that investors are familiar with construction principles, but less familiar with underlying risks and drivers of performance, suggesting that providers do not offer a lot of information on performance drivers and risks.

In addition, it appears from the survey that respondents allocate fewer resources for the evaluation of alternative beta compared to the evaluation of active managers. The evaluation of advanced beta offerings is firstly based on the use of independent research and on research published by providers, as well as on analytic tools, while meeting with providers is more important to evaluate active managers.

Respondents also see more challenges in evaluating smart beta offerings compared to active managers or cap-weighted indexing products. The lack of access to data, in particular live and after-cost performance, and the lack of transparency on the methodology are seen as key challenges. The evaluation of the risks of the strategies is also a big challenge in the evaluation process. Strategy-specific risks and specific risks related to factor tilts appear to be the most important risk for survey respondents, while the relative risk of underperforming cap-weighting indexes periodically is the least important risk for them. Further, all respondents agree that information about risk is not widely available from product providers, whatever the risk dimension. Costs and transparency are crucial for respondents to evaluate strategies, and theoretical justification is about as important to them as live performance.

In terms of implementation, respondents agree that advanced beta has strong diversification potential of various strategies, but also assert that well-designed offerings for this

EXHIBIT 2

Please indicate your satisfaction level with the following offerings

The satisfaction was rated from -2 (not at all satisfied) to +2 (highly satisfied). Only categories that respondents invest in according to their previous answers (see Exhibit A) are displayed. This exhibit gives the average score obtained for each strategy.

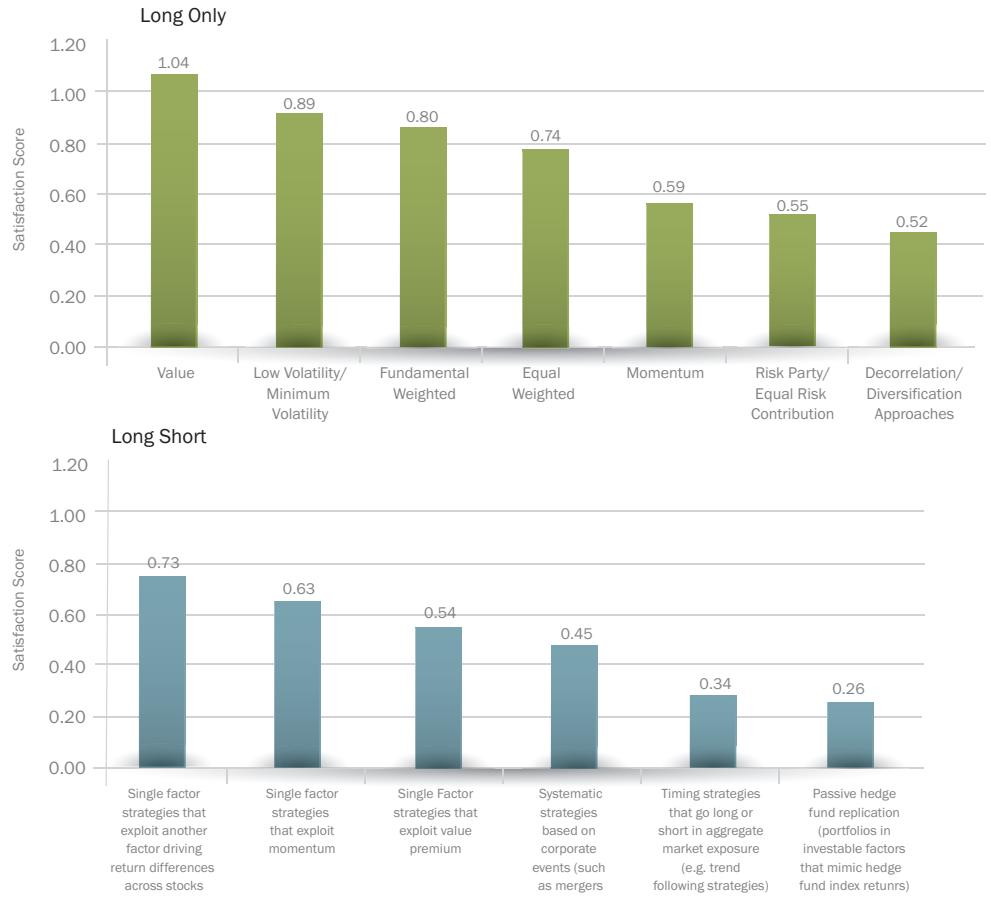
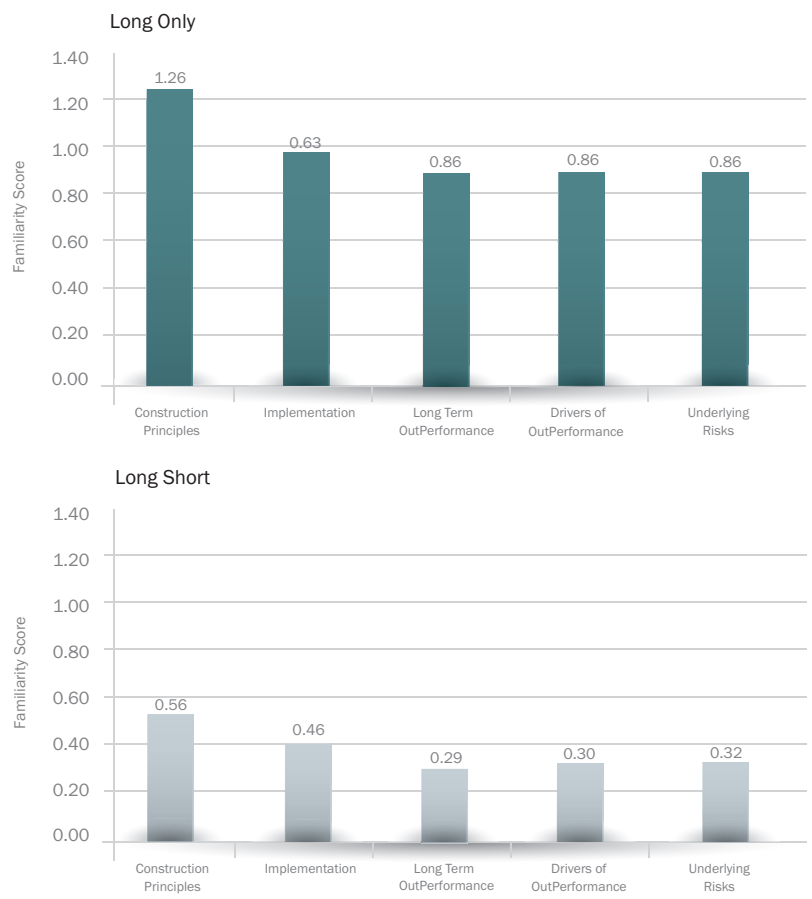


EXHIBIT 3

Which alternative equity beta strategies are you familiar with?

For each alternative equity beta strategy, respondents were asked to rate each aspect, including construction principles, implementation, long-term outperformance, drivers of outperformance and underlying risks. The familiarity was rated from -2 (do not know about the topic) to +2 (very familiar). The exhibit displays the average score across all strategies.



[16] These two arguments were respectively rated 1.22 and 1.13, on average, on a scale from -2 (strong disagreement) to +2 (strong agreement).
[17] These motivations were respectively rated 3.74, 3.50, 3.07 and 3.04, on average, on a scale from 1 (weak motivation) to 5 (strong motivation).

use are not widely available yet, which prevents them from using alternative beta strategies in this way. It appears that respondents prefer long-only strategies to gain exposure to alternative risk premia, in particular due to perceived implementation hurdles for long/short strategies.

The importance of factors as performance drivers

According to respondents, the performance of alternative beta strategies is explained by factor tilts.[18] Thus, factors are seen as the main performance driver for alternative beta. To a lesser extent, respondents also consider that the performance of alternative equity beta strategies is partly explained by rebalancing effects, as well as diversification.[19] Respondents are less convinced that the performance of alternative equity beta strategies is the result of data mining.[20] Value and small cap are the two factors considered by respondents as the most likely to be rewarded in the next 10 years.[21]

Finally, according to respondents, the important characteristics for factor-tilted strategies are not only to provide the highest possible correlation with a factor, while maintaining neutral exposure to other risk factors, but also to provide the best ease of implementation at a low cost, and to achieve the best possible reward for a given factor. At the same time, it appears that current products are seen as inadequate for these requirements, with the worst score being obtained by the ability of current products to hedge undesired risk exposures.

Key challenges for advanced equity beta investing

Overall, our survey respondents' answers to an extensive questionnaire on their use and perception of smart beta show that respondents have an overwhelming interest in advanced beta equity strategies. However, across the various sections of the questionnaire, respondents raised important concerns and several challenges regarding advanced beta investing in practice. While it is beyond the scope of this article to provide a detailed discussion and report on the results of our survey, we can provide an overview of the main challenges. In fact, across answers to different questions in our survey, the following 10 key conclusions emerge:

1. Investors are familiar with the construction principles of advanced beta strategies (rated 1.04, on average, on a scale from -2 (totally disagree) to +2 (completely agree)), but less familiar with underlying risks and drivers of performance (respectively rated 0.39 and 0.27, on average).[22]
2. Respondents allocate relatively few resources to the evaluation of alternative beta. The average respondent uses fewer than two full-time staff (1.77) to evaluate alternative beta offerings, a much lower number than that used to evaluate active managers (3.42).[23]
3. Respondents see bigger challenges with evaluating advanced beta offerings, with an average score of 3.21 on a scale from 1 (weak challenge) to 5 (very strong challenge), than with evaluating active managers or cap-weighted indexing products, with average scores of 2.02 and 2.87, respectively.[24]
4. Lack of access to data, rated 3.15 on average, on a scale from 1 (weak challenge) to 5 (very strong challenge), in particular live and after-cost performance, rated 3.63 and 3.34, respectively, on average, and analytics, rated 2.95 on average, are seen as key challenges.
5. For all types of risks, respondents agree that information is not widely available from product providers. The risk rated as the most important (risk related to factor tilt, rated 0.77, on average, on a scale from -2 (totally unimportant) to +2 (highly important)) is also one of those with the least information available according to respondents, who give a score of -0.10 on average to the availability of the information on a scale from -2 (strongly disagree that information is widely available) to +2 (strongly agree that information is widely available).[25]
6. Respondents' answers show that the theoretical justification of a strategy is seen as about as important as live performance, rated 1.14 and 1.24, respectively, on a scale from -2 (strongly disagree that it is important) to +2 (strongly agree) highlighting the need for product providers to focus not only on recent performance but also on the fundamental economic reasons for a strategy's performance benefits.[26]
7. Implementation is a key aspect for respondents, who commonly use a wide array of measures to assess implementation of alternative equity beta strategies (turnover, transaction costs, etc.), implying that product providers need to carefully consider implementation in product design.[27]
8. Respondents prefer long-only strategies to gain exposure to alternative risk premia, in particular due to perceived implementation hurdles for long/short strategies. Long-only-tilted strategies obtained an average score of 1.01 for ease of implementation on a scale from -2 (weakly prefer) to +2 (strongly prefer), compared with 0.35 for long/short strategies.[28]
9. While respondents agree that advanced beta has strong diversification potential through various strategies, with an average score of 0.84 on a scale from -2 (strongly disagree) to +2 (strongly agree), they also agree that well-designed offerings for this use are not widely available yet, with an average score of -0.12 on a scale from -2 (strongly disagree) to +2 (strongly agree), which prevents them from using alternative beta strategies in this way.[29]
10. Respondents require more from factor investing strategies than simply providing the right direction of exposure, rated 1.24 on a scale from -2 (not at all important) to +2 (important), notably to provide an efficient risk-adjusted return for a factor exposure, rated 0.93, with ease of implementation, rated 1.17. Current products are seen as insufficient for these requirements, as the achievement by current products of these requirements are rated 0.49, 0.19 and 0.25, respectively, on a scale from -2 (not fulfilled at all) to +2 (completely fulfilled).[30]

The robustness of the answers given by respondents in this survey was tested by considering the results by category of respondents, according to their activity, their country and the size of the company. Similar results were obtained from whatever the category respondents belong to, proving that the results of this survey are quite robust, as they are not related to a specific category of respondents.

While our survey results suggest that advanced beta equity investing is a promising avenue for the investment industry, our results also contain a note of caution, in that there is a risk that the good idea of advanced beta equity investing may end up being compromised by practical investment challenges and perceived insufficiencies of current products, notably in the form of insufficient transparency and insufficient information. These results confirm earlier research on the need for transparency of index investors in general (see Amenc and Ducoulombier, 2014). Moreover, investors' responses to our survey suggest that they are likely to require more education not only on the benefits but also on the risks of advanced beta investing, the need to dedicate sufficient resources to due diligence on the buy side, to have access to readily available strategy and factor combinations, and to have more suitable factor investing products. We hope that our survey provides food for thought for both investors and product providers, and helps to raise awareness on issues that need to be addressed for advanced beta strategies to reach their full potential. •

The research from which this article was drawn was produced as part of the Newedge "Advanced Modeling for Alternative Investments" research chair at EDHEC-Risk Institute.

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[18] This argument was rated 1.04, on average, on a scale from -2 (totally disagree) to +2 (completely agree).
[19] These two arguments were respectively rated 0.39 and 0.27, on average, on a scale from -2 (totally disagree) to +2 (completely agree).
[20] This argument was rated -0.20, on average, on a scale from -2 (totally disagree) to +2 (completely agree).
[21] These two factors obtained a score of 3.28 and 2.93, respectively, on a scale from 0 (no confidence) to 5 (high confidence).
[22] For each alternative equity beta strategy, respondents were asked to rate each aspect, including construction principles, implementation, long-term outperformance, drivers of outperformance and underlying risks.
[23] Respondents were asked for the number of full-time staff mainly concerned with the evaluation of advanced beta offerings, the evaluation of cap-weighted indexes and passive investment products and the evaluation of active managers.
[24] Concerning the evaluation of investment strategies and products, including advanced beta offerings, cap-weighted indexes and passive investment products and active managers, respondents were asked to indicate what they see as a challenge among the following: lack of transparency on methodology, lack of access to data, lack of availability of live track records, lack of after-cost performance data, lack of availability of analytics and lack of availability of independent research.
[25] Respondents were asked to evaluate the relative importance of the various dimensions of risks in the assessment of alternative equity beta strategies and to give their opinion about the availability of information on each type of risk.
[26] Respondents were asked to indicate their agreement with the importance of a list of proposals concerning alternative equity beta strategies.
[27] Respondents were asked to indicate the measures they use to assess implementation aspects of alternative equity beta strategies.
[28] Respondents were asked to indicate the method they prefer, based on a list of criteria, to gain exposure to alternative risk premia.
[29] Respondents were asked to express their agreement with a list of statements relating to the combination of alternative equity beta strategies.
[30] Respondents were asked which requirements they consider to be important for a factor-tilted alternative equity beta strategy and to indicate if currently available products fulfill each requirement.

INDEXES

Examining Geographic Exposure in Performance Attribution and Reporting

Noël Amenc
Professor of Finance, EDHEC Business School; Director EDHEC-Risk Institute; and CEO, ERI Scientific Beta

Kumar Gautam
Quantitative Equity Analyst
ERI Scientific Beta

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

Nicolas Gonzalez
Senior Quantitative Analyst
ERI Scientific Beta

Performance and risk reports of equity portfolios frequently report a breakdown of portfolio holdings by geography, based on simple markers such as the stock's primary listing and the firm's place of incorporation and headquarters. However, it is questionable whether these markers are relevant for the underlying geographic exposure of a stock. For example, should an automaker who is listed, headquartered and incorporated in Germany, and sells his cars mainly to the U.S. and China, be considered as providing exposure to Germany, or even to Europe? Should stock of a Swiss-listed and headquartered pharmaceutical company that sells its products worldwide be considered to provide exposure to Switzerland or even to Europe? Beyond such examples, in a world of increasing globalization, it is clear that the typical markers used for labeling firms as belonging to a certain country lose their relevance. In fact, even the practice of assigning a unique nationality for each stock seems obsolete in a world with multinational corporations. This question has numerous implications, whether involving performance attribution or geographical risk measurement for portfolios, and of course for investors and managers' strategic or tactical allocation choices.

At the same time, changes in accounting standards have made firm-level data on business activity across geographic segments much more widely available over the recent decade. Given the rich information available on the breakdown of sales in particular, a natural question is whether such data can be used to obtain more meaningful geographic exposure reporting of equity portfolios. In this article, we analyze the usefulness of a company's reported geographic segmentation data (total sales disaggregated into sales from different geographies) in performance reporting. First, we analyze the application of geographic segmentation data in reporting the geographic exposure (proportion of sales coming from different geographies) of equity portfolios. Second, we analyze the application of geographic segmentation data in performance attribution, where we attribute the performance of a developed market index to the performance of portfolios having varied levels of exposure to emerging markets (or official regional markets).

We use and extend early research on geographic segmentation data (see e.g., Roberts, 1989, Balakrishnan et al., 1990 and Ahadiat, 1993 on the use of segmented data for forecasting earnings) to reporting geographic risk exposure and performance attribution. While we have conducted a similar analysis on the U.S. and Asian stock market indexes, in this article we illustrate our methodology and results using selected European indexes. We mainly focus on the STOXX Europe 600 index representing large and medium-sized securities from 18 developed European countries. Section 1 describes data and methodology. Section 2 and Section 3 demonstrate applications of geographic segment data. We provide a complimentary analysis focusing on a UK index, the FTSE 100, in a separate box. Finally, section 4 concludes.

Section 1: Data and methodology

We report geographic exposure of the index constituents at the end of June every year over 10 years (2004 to 2013). For the index constituents as of June t, we consider sales for fiscal year t-1 in order to avoid look-ahead bias.

The source of geographic segmentation data is DataStream (Worldscope). It provides geographic breakdown of sales as reported by companies.

We report the geographic exposure of index to four regions (Americas, Europe, Middle East & Africa and Asia & Pacific) as well as to developed and emerging markets. To determine countries that constitute the above-mentioned four regions, we rely on United Nations Statistics Division (UNSD)[31], which groups individual countries (economies) into sub-regions, further aggregated into geographic regions (continents). UNSD does not have any standard methodology to classify countries into developed and emerging market, thus the classification of countries into developed or emerging is based on ERI Scientific Beta's methodology.[32] Arguably, the countries in the United Nations' list that are not categorized by ERI Scientific Beta have been grouped into the emerging market category.

Mapping reported geographic sales to individual countries: If a company reports sales per country, it is fairly simple to assign it to any of the four regions (based on UNSD classification) and to either the developed or emerging category (based on Scientific Beta classification). However, companies can also report sales from sub-regions (e.g., North America and South America), regions (e.g., Americas), special economic or political groupings (e.g., European Union) or mix of these (e.g., Brazil and North America).

In such cases, to achieve our objective, which is to report sales of index constituents from the four mentioned regions and from developed and emerging market, we follow a two-step process. First, we disaggregate sales for each reported geographic segment into country-level sales. The proportion of sales assigned to a country within a region is the same as the weight of a country's GDP[33] in the total GDP of the geography (Li et al., 2014). Second, we aggregate country-level sales back to sales from four regions and from developed and emerging market.

Section 2: Geographic segmentation: an application to reporting

In this section we analyze the geographic exposure of the STOXX Europe 600 index. First, we report geographic exposure of the index to four regions (Africa & Middle East, Americas, Asia & Pacific and Europe) and then to developed and emerging markets.

Before we move forward, in Exhibit 1 we report the non-European and emerging market exposure of the top 50 companies in the STOXX Europe 600 by market capitalization. The aim is to provide a fair idea of the geographic exposure of the overall index by focusing on some of the largest companies in the index.

Note that most of the large companies listed above have significant exposure to both non-European and emerging markets. For example, for the fiscal year 2012, around 71% and 33% of Nestle's sales came from non-European and emerging markets, respectively. There are a few large companies that have low exposure to non-European and emerging markets. For example, companies such as Lloyds Banking Group, Nordea Bank and EDF have less than 10% exposure to non-European and emerging markets.

Overall, the figures suggest that a significant amount of sales of most of the largest companies in the STOXX Europe 600 comes from non-European and emerging markets, whereas the index itself is labeled as representing developed Europe, which highlights the need to report geographic exposure of the index.

Geographic exposure to regions through time

In this sub-section we analyze the geographic exposure of the STOXX Europe 600 to the four regions mentioned above. Before starting the discussion on the overall exposure of the index, in Exhibit 2 below we list the top 10 companies in the STOXX Europe 600 that have the highest exposure to non-European markets.

Note that for all the companies in the table, almost the entire revenue — 97%-100% — comes from non-European markets, although they are labeled as European companies. Clearly, it raises questions about the current practice of reporting geographic exposure of equity portfolios based on simplistic measures such as place of listing of the stock or a firm's incorporation.

In exhibit 3, we report the exposure of STOXX Europe 600 companies to the four regions. We note that the percentage of sales of companies in the STOXX Europe 600 from Europe, its "local market," has fallen from 64% in FY 2003 to 55% in FY 2012. At the same time, the exposure of European companies to Asia Pacific has doubled from 8% to 16%. Also, the exposure of European companies to Africa and Middle East has doubled from 2% to 4%. The exposure to Americas has declined, although less significantly, from 27% to 25%.

The observations tell us that the exposure of companies in the STOXX Europe 600 to non-European markets is significant and has steadily increased over the past years, highlighting the need to report the exposure of equity portfolios to different regions.

Exposure to developed/emerging markets through time

Here we analyze the geographic exposure of the STOXX Europe 600 to emerging and developed markets. Consistent with the previous sub-section, we list the top 10 companies in the STOXX Europe 600 that have the highest exposure to emerging markets. In Exhibit 4, note that for six out of 10 companies, the entire revenue comes from emerging markets. For the other four, over 80% of the revenue comes from emerging markets. This again highlights the importance of reporting exposure of equity portfolios not just in terms of place of listing of the stock or incorporation, but also based on the geographic source of revenue.

In exhibit 5, we report the exposure of STOXX Europe 600 companies to developed and emerging markets. Note that the percentage of sales of companies in the STOXX Europe 600 to developed markets has fallen from 89% in FY 2003 to 77% in FY 2012. To put it another way, the exposure of companies in the STOXX Europe 600 to emerging markets has more than doubled, from 11% to 23%, from FY 2003 to FY 2012.

It is worth mentioning that although the STOXX Europe 600 is labeled a developed market index, its exposure to emerging markets is significant and has increased consistently in recent years. This development highlights the need to report exposure of equity portfolios in terms of their exposure to developed and emerging markets.

To provide a different perspective on "local" versus "foreign" exposure in the STOXX index for developed Europe, we report in the table below the weight of constituents in the STOXX Europe 600 that have more than 50% and less than 50% exposure to developed Europe, which is the index's local market. Interestingly, we note that the weight of stocks that have more than 50% exposure to developed Europe has declined over the 10-year period from around 56% to 35%. At

[31] Source: http://unstats.un.org/unsd/methods/m49/m49regin.htm
[32] Source: http://www.scientificbeta.com/#/tab/article/eri-scientific-beta-universe-construction-rules
[33] Source: http://unstats.un.org/unsd/snaama/dnllist.asp

the same time, the weight of stocks with less than 50% exposure to developed Europe has increased from around 44% to 65%.

The figures above can be summarized by the key finding that the role of companies in the STOXX Europe 600 with more "local" sales than "foreign" sales has significantly declined over the years, reflecting the need to report the exposure of the index using geographic segmentation data.

Section 3: Application to performance attribution

In this section we turn to a discussion of the effects that exposure to emerging and foreign markets has on the performance of the STOXX Europe 600. In particular, we attribute index performance to the performance of stocks with different levels of geographic exposure. We use the following methodology for performance attribution.

We sort stocks at the end of June every year by their percentage of total sales coming from emerging (or official regional) markets. We then create three portfolios: the top portfolio and bottom portfolio have the stocks with the highest and lowest sales exposure to emerging (or official regional) markets, respectively, where the number of stocks is such that each portfolio's market capitalization is 33% of the index's total market capitalization. The middle portfolio comprises the remaining stocks.

The attribution of the index return into three portfolios is done using the Ordinary Least Square regression as explained below.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_1 (R_{P_{1,t}} - R_{f,t}) + \beta_2 (R_{P_{2,t}} - R_{f,t}) + \beta_3 (R_{P_{3,t}} - R_{f,t}) + \varepsilon_t, \qquad t = 1, \ldots, T$$

where, $R_{i,t}$ and $R_{f,t}$ are the return on the index and the risk-free rate, respectively. $R_{P1,t}$, $R_{P2,t}$ and $R_{P3,t}$ are returns on the top portfolio, middle portfolio and bottom portfolio respectively.

The contribution of a portfolio towards the excess return of the index is computed as:

$$C_i = \beta_i \times \left[\left(\prod_{t=1}^{T} 1 + (R_{P_{1,t}} - R_{f,t}) \right) - 1 \right]$$

where, C_i is the contribution of portfolio i and $i \in \{1, 2, 3\}$. The unexplained performance is the difference of the excess return of the index and the sum of the contributions of each of the portfolios.

By construction, as the three portfolios represent equal market capitalisation of the index, any deviation from an equal contribution to the return of the index reflects outperformance (or underperformance) of a portfolio relative to other portfolios, each having different levels of exposure to emerging (or official regional) market.

Contribution of emerging market exposure to the performance of the STOXX Europe 600

In this sub-section, we analyse the performance attribution of the STOXX Europe 600 to portfolios formed by sorting stocks based on their level of sales in emerging markets. In Exhibit 7 below, we note that there are certain periods when the difference in contribution of high and low emerging-market-exposed stocks to the performance of the STOXX Europe 600 is not large but there are also periods when the difference in contribution is large.

For example, from July 2007 to June 2008, the contributions of the high and low emerging- market-exposure portfolio were 0.06% and -6.20% respectively. The financial crisis unfolded during this period in developed markets and the performance of developed market equities was negative (the return on MSCI World, representing developed markets, was -10.18%) while the performance of emerging market equities was positive (the return on MSCI Emerging, representing emerging markets, was 4.86%). Likewise, in the following year (2008-09), while both high and low emerging-market-exposed stocks contributed negatively, the negative contribution of high emerging-market-exposed stocks was limited compared to stocks with low emerging-market exposure, which is consistent with the overall underperformance of broader developed market equity as compared to broader emerging market equity. The observations above highlight the importance of analysing the performance of portfolios in terms of geographic risk exposure.

Contribution of official regional market exposure to the performance of the STOXX Europe 600

Here we analyse performance attribution of the STOXX Europe 600 to the portfolios formed by sorting stocks based on their exposure to the index's official regional market (developed Europe). In Exhibit 8 we note that there are certain periods when the difference in contribution of high and low Developed-Europe-exposed stocks to the performance of the STOXX Europe 600 is not large, but there are also periods when the difference in contribution is significantly large.

For example, from July 2007 to June 2008, the negative contribution of stocks with high exposure to Developed Europe was of higher magnitude (-7.04%) than the negative contribution of stocks with low exposure to Developed Europe (-2.92%).

EXHIBIT 1

Non-European and emerging market exposure of Top 50 companies (by market capitalization weight) in STOXX Europe 600

The table below lists the non-European market and emerging market sales, as % of total sales, of the top 50 companies in the STOXX Europe 600 by market capitalization. The index constituents and market capitalization weight is as of end of June 2013, for which sales data is taken for fiscal year 2012. The source of geographic segmentation data is DataStream (Worldscope). If a company reports sales for a region (other than country-level), we break down regional sales to country-level sales based on the GDP weight of the country in the region (see Section 1).

	Non-European sales (% of total sales)	Emerging market sales (% of total sales)
NESTLE R	70.80%	33.46%
HSBC HDG.	69.70%	26.91%
NOVARTIS R	70.83%	25.94%
ROCHE HOLDING	71.04%	20.37%
ANHEUSER-BUSCH INBEV	83.12%	41.00%
VODAFONE GROUP	29.29%	29.29%
SANOFI	68.36%	27.46%
BP	62.97%	20.41%
GLAXOSMITHKLINE	70.79%	28.20%
ROYAL DUTCH SHELL A	57.37%	26.54%
TOTAL	46.00%	25.43%
L'OREAL	52.44%	20.75%
BRITISH AMERICAN TOBACCO	66.66%	45.14%
SAP	68.81%	0.00%
SIEMENS	49.03%	22.32%
BAYER	58.80%	30.74%
LVMH	69.53%	34.20%
BASF	69.29%	28.39%
INDITEX	25.22%	12.75%
ENI	37.51%	39.39%
BANCO SANTANDER	57.15%	56.36%
NOVO NORDISK B	70.56%	13.70%
LLOYDS BANKING GROUP	4.22%	1.91%
BNP PARIBAS	27.60%	14.96%
ALLIANZ	40.03%	18.70%
UBS R	52.45%	7.03%
DAIMLER	67.27%	24.59%
UNILEVER CERTS.	72.96%	29.96%
ASTRAZENECA	71.26%	25.49%
TELEFONICA	50.46%	48.29%
BG GROUP	64.55%	23.25%
RIO TINTO	87.31%	49.53%
GLENCORE	49.21%	30.05%
BARCLAYS	54.44%	28.09%
BHP BILLITON	88.40%	52.14%
BMW	67.38%	37.24%
STANDARD CHARTERED	98.32%	37.37%
DEUTSCHE TELEKOM	30.44%	4.62%
UNILEVER	72.96%	29.96%
RECKITT BENCKISER GROUP	44.37%	50.10%
ABB LTD N	64.22%	34.28%
HENNES & MAURITZ B	38.05%	19.95%
DANONE	48.02%	25.88%
GDF SUEZ	20.87%	14.00%
AXA	41.61%	5.91%
BBV.ARGENTARIA	64.69%	52.73%
RICHEMONT N	76.51%	44.49%
NORDEA BANK	3.45%	7.66%
EDF	9.38%	4.24%
DEUTSCHE BANK	38.55%	17.52%

EXHIBIT 2

Companies in STOXX Europe 600 with highest exposure to non-European markets

The table below lists the companies which have the highest exposure (% of sales) to non-European markets. The table also lists the cap-weighted rank of the stock in the index. The index constituents and cap-weighted rank are as of end June, 2013, for which sales data is taken for fiscal year 2012. The source of geographic segmentation data is DataStream (Worldscope). If a company reports sales for a region (other than country-level sales), we break down regional sales to country-level sales based on the GDP weight of the country within the geography (see Section 1: Data and methodology).

Name	Non-European sales (% of total sales)	Cap-weighted rank in the index
FRESNILLO	100.00%	199
EXOR ORD	100.00%	257
ELAN	100.00%	263
ENAGAS	100.00%	306
RANDGOLD RESOURCES	100.00%	313
AFREN	100.00%	507
MAUREL ET PROM	100.00%	529
FLSMIDTH & CO.B	99.75%	488
STANDARD CHARTERED	98.32%	37
CHR HANSEN HOLDING	97.45%	364

EXHIBIT 3

STOXX Europe 600 (Regional Breakdown)

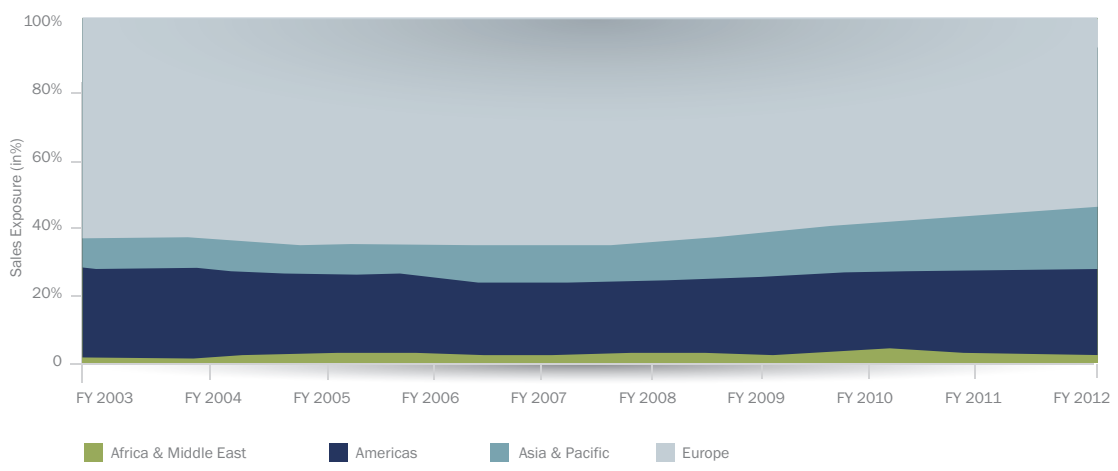

EXHIBIT 4

Companies in STOXX Europe 600 with highest exposure to emerging markets

The table below lists the companies that have the highest exposure (% of sales) to emerging markets. The table also lists the cap-weighted rank of the stock in the index. The index constituents and market capitalization are as of the end of June, 2013, for which sales data is taken for fiscal year 2012. The source of geographic segmentation data is DataStream (Worldscope). If a company reports sales for a region (other than country-level sales), we break down regional sales to country-level sales based on the GDP weight of the country with the geography (see Section 1).

Name	Non-European sales (% of total sales)	Cap-weighted rank in the index
FRESNILLO	100.00%	199
RANDGOLD RESOURCES	100.00%	313
AFREN	100.00%	507
MAUREL ET PROM	100.00%	529
COCA COLA HBC (ATH)	100.00%	229
INTERNATIONAL PSNL. FIN.	100.00%	518
ENAGAS	97.99%	306
TULLOW OIL	89.80%	153
POLYMETAL INTERNATIONAL	89.13%	471
VEDANTA RESOURCES	83.24%	391

Similarly, from July 2009 to June 2010, the contributions of high and low Developed-Europe-market-exposure portfolios were -1.36% and 6.57% respectively. Notably, in 2009, growth in the aggregate gross domestic product of economies in Europe was negative compared to the previous year, which perhaps can partly explain the reason behind the negative contribution of companies in the STOXX Europe 600 which have high sales exposure to European markets. The observation also highlights the usefulness of analysing the performance of equity portfolios in terms of geographic risk exposure.

Analysing the geographic exposure of the FTSE 100

We conduct an analysis similar to that for the STOXX Europe 600 on data for the FTSE 100. For this index, we define local exposure as exposure to the UK economy, and assess local versus foreign exposure. We also assess developed versus emerging exposure. Intuitively, one would expect heavier exposure to foreign markets compared to the results for the STOXX Europe 600 index, as the FTSE 100 has a narrower local market consisting of a single country. The sales exposure of UK companies to other Developed European markets would thus appear as foreign exposure, whereas in our analysis of the STOXX Europe 600 index, we would consider the exposure of UK companies to Developed Europe ex-UK as being local, given the index universe definition. Additionally, it is commonly recognised that the London Stock Exchange is a major listing venue for foreign companies, which should lead to a tendency to include companies with heavy foreign market exposure in the "local" index. Moreover, many UK companies, such as HSBC or Standard Chartered, traditionally have extensive operations in emerging markets. Indeed, when analysing the results for geographic exposure (Exhibits 9 and 10) and the return contribution of stocks with heavy foreign or emerging market exposure to the index, the influence of geographic exposure to non-UK and emerging companies tends to be even more pronounced than for the STOXX Europe 600 index.

Section 4: Conclusion

We analyze application of geographic segmentation data in reporting geographic exposure and performance attribution, by taking the example of the STOXX Europe 600. Although the index tracks companies in developed Europe, its exposure to non-European and emerging markets is significant and has increased in recent years. We also analyze the impact of such exposure on the performance of the STOXX Europe 600. We note that in certain years, the impact of such exposures on the performance of the index is noticeably high. Given the increasing availability of information on business activity (most notably sales) across geographic segments in company reports, it is possible to report the economic exposures implied in equity portfolios. Reporting this exposure is arguably more relevant than reporting a breakdown based on nationality labels that seem artificial in a globalized economy. •

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EXHIBIT 5

STOXX Europe 600 (Developed/Emerging Breakdown)

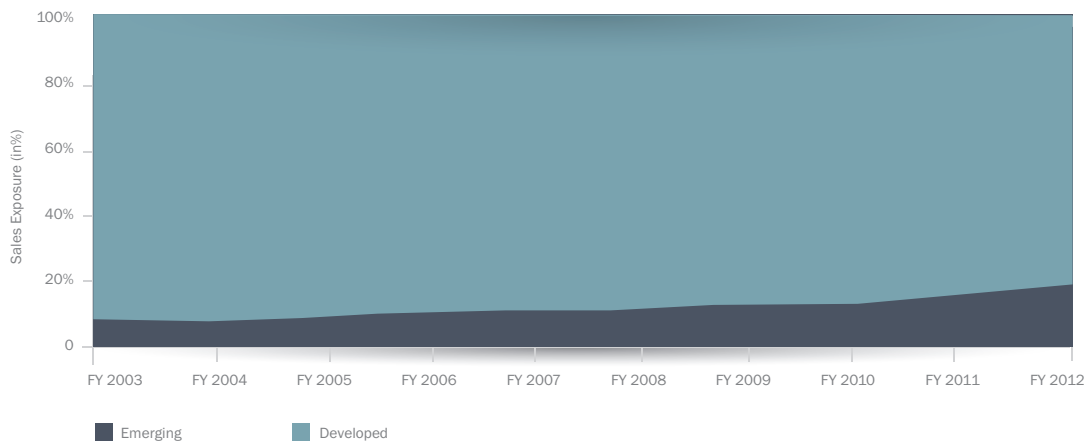


EXHIBIT 6

Weight of stocks with > 50% and < 50% Developed Europe exposure in STOXX Europe 600

The table below reports weight of stocks in the STOXX Europe 600 index with more than 50% and less than 50% exposure to Developed Europe. The weights represent market capitalisation weight at the end of June every year. The currency used is US$. The exposure is calculated using segment sales data for the previous fiscal year. The source of geographic segmentation data is DataStream (Worldscope).

	Weight of stocks with > 50% Developed Europe exposure	Weight of stocks with < 50% Developed Europe exposure
2003	56.39%	43.61%
2004	55.60%	44.40%
2005	58.67%	41.33%
2006	57.47%	42.53%
2007	57.06%	42.94%
2008	55.58%	44.42%
2009	48.59%	51.41%
2010	45.11%	54.89%
2011	37.55%	62.45%
2012	35.05%	64.95%

EXHIBIT 7

Return contribution to STOXX Europe 600 of stocks with varying emerging market exposure:

The table below reports the breakdown of the annualised excess return of the STOXX Europe 600 into the performance of three portfolios formed by sorting stocks based on their sales exposure to emerging markets. To form portfolios, we sort stocks by their emerging market sales exposures. We then select the top stocks up to 33% of cumulative market cap (High), and the bottom stocks up to 33% cumulative market cap (Low), and form high and low-exposure cap-weighted portfolios based on these sorts. Stocks which are not included in either extreme portfolio form the medium portfolio (Mid). The portfolios are formed at the end of June every year, using geographic segmentation data for the previous fiscal year. The statistics are based on daily total return series (with dividends reinvested) in USD. The portfolio constituents are weighted by their total market capitalisation in (USD) at the end of June every year. The figures for High and Low portfolios are highlighted in bold. For performance attribution, we use OLS regression, wherein the dependent variable is excess return on the STOXX Europe 600 and independent variables are excess return on the High, Mid and Low portfolios. All returns are in excess of the risk-free rate. The risk-free rate in US Dollars is measured using return on the Secondary Market US Treasury Bills (3M). The source of geographic segmentation data is DataStream (Worldscope).

	STOXX Europe 600	High	Mid	Low	Unexplained
July 2004 - June 2005	15.19%	**4.53%**	4.03%	**5.74%**	0.89%
July 2005 - June 2006	22.06%	**7.92%**	7.06%	**5.84%**	1.24%
July 2006 - June 2007	28.55%	**8.98%**	9.37%	**9.71%**	0.49%
July 2007 - June 2008	-14.03%	**0.06%**	-7.42%	**-6.20%**	-0.46%
July 2008 - June 2009	-34.35%	**-7.48%**	-16.60%	**-11.57%**	1.31%
July 2009 - June 2010	6.62%	**2.92%**	3.45%	**-0.52%**	0.78%
July 2010 - June 2011	37.11%	**15.22%**	14.43%	**7.81%**	-0.35%
July 2011 - June 2012	-16.11%	**-5.32%**	-7.36%	**-4.53%**	1.09%
July 2012 - June 2013	20.34%	**3.94%**	11.01%	**5.90%**	-0.51%
July 2013 - June 2014	30.35%	**8.85%**	10.78%	**10.98%**	-0.25%

EXHIBIT 8

Return contribution to STOXX Europe 600 of stocks with varying official regional market exposure:

The table below reports the breakdown of the annualised excess return of the STOXX Europe 600 into the performance of three portfolios formed by sorting stocks based on their sales exposure to Developed Europe To form portfolios, we sort stocks by their Developed Europe sales exposures. We then select the top stocks up to 33% of cumulative market cap (High), and the bottom stocks up to 33% cumulative market cap (Low), and form high and low-exposure cap-weighted portfolios based on these sorts. Stocks which are not included in either extreme portfolio form the medium portfolio (Mid). The portfolios are formed at the end of June every year, using geographic segmentation data for the previous fiscal year. The statistics are based on daily total return series (with dividends reinvested) in USD. The portfolios constituents are weighted by their total market capitalisation in (USD) at the end of June every year. The figures for High and Low portfolios are highlighted in bold. For performance attribution, we use OLS regression, wherein the dependent variable is excess return on the STOXX Europe 600 and independent variables are excess return on the High, Mid and Low portfolios. All returns are in excess of the risk-free rate. The risk-free rate in US Dollars is measured using the return on the Secondary Market US Treasury Bills (3M). The source of geographic segmentation data is DataStream (Worldscope).

	STOXX Europe 600	High	Mid	Low	Unexplained
July 2004 - June 2005	15.19%	**5.46%**	4.25%	**4.40%**	1.08%
July 2005 - June 2006	22.06%	**6.20%**	6.57%	**7.98%**	1.31%
July 2006 - June 2007	28.55%	**8.96%**	11.84%	**7.33%**	0.43%
July 2007 - June 2008	-14.03%	**-7.04%**	-2.82%	**-2.92%**	-1.25%
July 2008 - June 2009	-34.35%	**-14.95%**	-7.52%	**-13.67%**	1.80%
July 2009 - June 2010	6.62%	**-1.36%**	1.39%	**6.57%**	0.02%
July 2010 - June 2011	37.11%	**9.34%**	13.15%	**14.74%**	-0.12%
July 2011 - June 2012	-16.11%	**-6.23%**	-6.41%	**-3.72%**	0.26%
July 2012 - June 2013	20.34%	**6.72%**	5.55%	**7.81%**	0.26%
July 2013 - June 2014	30.35%	**11.61%**	10.35%	**8.63%**	-0.24%

EXHIBIT 9

Non-UK and emerging market exposure of the top 50 companies (by market capitalisation weight) in the FTSE 100

The table below lists the non-UK and emerging market sales, as % of total sales, of the top 50 companies in the FTSE 100 by market capitalisation. The index constituents and market capitalisation weight is as of end of June 2013, for which sales data is taken for fiscal year 2012. The source of geographic segmentation data is DataStream (Worldscope). If a company reports sales for a region (other than country-level sales), we break down regional sales to country-level sales based on the GDP weight of the country with the geography (see Section 1).

	Non-UK sales (% of total sales)	Emerging market sales (% of total sales)
HSBC HDG. (ORD $0.50)	95.63%	26.91%
VODAFONE GROUP	84.14%	29.29%
BP	79.93%	20.41%
GLAXOSMITHKLINE	94.23%	28.20%
ROYAL DUTCH SHELL A	93.86%	26.54%
BAT	100.00%	45.14%
LLOYDS BANKING GROUP	5.81%	1.91%
ASTRAZENECA	93.41%	25.49%
BG GROUP	83.88%	23.25%
RIO TINTO	98.78%	49.53%
GLENCORE	92.68%	30.05%
BARCLAYS	69.90%	28.09%
BHP BILLITON	98.68%	52.14%
STANDARD CHARTERED	98.32%	37.37%
UNILEVER (UK)	100.00%	29.96%
RECKITT BENCKISER	91.98%	50.10%
PRUDENTIAL	59.11%	11.45%
NATIONAL GRID	56.62%	0.00%
TESCO	32.92%	11.67%
BT GROUP	23.52%	7.03%
ROLLS-ROYCE HOLDINGS	83.50%	28.64%
CENTRICA	29.03%	2.40%
ROYAL BANK OF SCTL.GP.	52.14%	9.38%
COMPASS GROUP	95.86%	19.70%
WPP	87.71%	23.77%
SSE	2.06%	0.33%
ASSOCIATED BRIT.FOODS	57.17%	18.91%
BRITISH SKY BCAST.GP.	6.16%	2.02%
BAE SYSTEMS	76.33%	18.41%
SHIRE	95.58%	13.06%
EXPERIAN	83.09%	27.04%
ARM HOLDINGS	85.81%	13.61%
TULLOW OIL	98.81%	89.80%
WOLSELEY	85.86%	5.54%
STANDARD LIFE	34.64%	5.77%
KINGFISHER	63.16%	13.01%
ANTOFAGASTA	99.42%	42.28%
NEXT	1.44%	1.02%
MARKS & SPENCER	10.73%	3.53%
LAND SECURITIES GROUP	0.00%	0.00%
SAINSBURY (J)	0.00%	0.00%
SMITH & NEPHEW	92.82%	23.96%
FRESNILLO	100.00%	100.00%
CAPITA	3.58%	1.18%
MORRISON(WM)SPMKTS.	0.00%	0.00%
BURBERRY GROUP	74.63%	32.89%
ITV	13.71%	4.51%
WHITBREAD	2.73%	0.90%
JOHNSON MATTHEY	66.79%	19.79%
SMITHS GROUP	95.09%	15.64%

EXHIBIT 10

Weight of stocks with > 50% and < 50% United Kingdom exposure in the FTSE 100

The table below reports the weight of stocks in the FTSE 100 index with more than 50% and less than 50% exposure to the United Kingdom. The weights represent market capitalisation weight at the end of June every year. The currency used is US$. The exposure is calculated using segment sales data for the previous fiscal year. The source of geographic segmentation data is DataStream (Worldscope).

	Weight of stocks with > 50% UK exposure	Weight of stocks with < 50% UK exposure
2003	28.85%	71.15%
2004	29.11%	70.89%
2005	31.91%	68.09%
2006	33.16%	66.84%
2007	21.85%	78.15%
2008	18.35%	81.65%
2009	16.55%	83.45%
2010	15.73%	84.27%
2011	14.75%	85.25%
2012	16.80%	83.20%

EXHIBIT 11

Return contribution to the FTSE 100 of stocks with varying local market exposure:

The table below reports the breakdown of the annualized excess return of the FTSE 100 into the performance of three portfolios formed by sorting stocks based on their sales exposure to the UK. To form portfolios, we sort stocks by their UK sales exposures. We then select the top stocks up to 33% of cumulative market cap (High), and the bottom stocks up to 33% of cumulative market cap (Low) and form high and low-exposure cap-weighted portfolios based on these sorts. Stocks that are not included in either extreme portfolio form the medium portfolio (Mid). The portfolios are formed at the end of June every year, using geographic segmentation data for the previous fiscal year. The statistics are based on daily total return series (with dividends reinvested) in US$. The portfolio constituents are weighted by their total market capitalization in US$ at the end of June every year. The figures for High and Low portfolios are highlighted in bold. For performance attribution, we use OLS regression, wherein the dependent variable is the excess return on the FTSE 100 and independent variables are the excess return on the High, Mid and Low portfolios. All returns are in excess of the risk-free rate. The risk-free rate in US$ is measured using the return on the Secondary Market U.S. Treasury Bills (3M). The last column reports t-stats for the null hypothesis that the mean of difference in daily returns of high and low portfolios is zero. The source of geographic segmentation data is DataStream (Worldscope) supplemented by Bloomberg.

	FTSE 100	High UK exposure	Mid UK exposure	Low UK exposure	Unexplained
July 2004 - June 2005	14.85%	**4.74%**	5.31%	**4.69%**	0.11%
July 2005 - June 2006	17.46%	**5.91%**	3.06%	**9.34%**	-0.85%
July 2006 - June 2007	21.98%	**9.19%**	8.32%	**4.01%**	0.46%
July 2007 - June 2008	-15.20%	**-10.92%**	-1.92%	**0.18%**	-2.53%
July 2008 - June 2009	-35.02%	**-8.86%**	-14.55%	**-10.89%**	-0.72%
July 2009 - June 2010	8.71%	**-1.93%**	4.44%	**6.18%**	0.03%
July 2010 - June 2011	33.76%	**8.65%**	12.15%	**11.74%**	1.21%
July 2011 - June 2012	-4.94%	**-2.92%**	1.65%	**-3.88%**	0.22%
July 2012 - June 2013	11.91%	**8.14%**	3.97%	**1.03%**	-1.23%
July 2013 - June 2014	26.50%	**7.94%**	11.45%	**6.01%**	1.09%

EXHIBIT 12

Return contribution to the FTSE 100 of stocks with varying emerging market exposure:

The table below reports the breakdown of the annualized excess return of the FTSE 100 into the performance of three portfolios formed by sorting stocks based on their sales exposure to emerging markets. To form portfolios, we sort stocks by their emerging markets sales exposures. We then select the top stocks up to 33% of cumulative market cap (High), and the bottom stocks up to 33% of cumulative market cap (Low), and form high and low-exposure cap-weighted portfolios based on these sorts. Stocks that are not included in either extreme portfolio form the medium portfolio (Mid). The portfolios are formed at the end of June every year, using geographic segmentation data for the previous fiscal year. The statistics are based on daily total return series (with dividends reinvested) in US$. The portfolio constituents are weighted by their total market capitalization in US$ at the end of June every year. The figures for High and Low portfolios are highlighted in bold. For performance attribution, we use OLS regression, wherein the dependent variable is the excess return on the FTSE 100 and the independent variables are the excess return on High, Mid and Low portfolios. All returns are in excess of the risk-free rate. The risk-free rate in US$ is measured using the return on the Secondary Market U.S. Treasury Bills (3M). The last column reports t-stats for the null hypothesis that the mean of difference in daily returns of high and low portfolios is zero. The source of geographic segmentation data is DataStream (Worldscope) supplemented by Bloomberg.

	FTSE 100	High Emerging exposure	Mid Emerging exposure	Low Emerging exposure	Unexplained
July 2004 - June 2005	14.85%	**3.25%**	5.22%	**6.39%**	-0.01%
July 2005 - June 2006	17.46%	**6.81%**	5.24%	**5.78%**	-0.37%
July 2006 - June 2007	21.98%	**6.86%**	4.46%	**10.29%**	0.37%
July 2007 - June 2008	-15.20%	**2.61%**	-5.67%	**-9.89%**	-2.25%
July 2008 - June 2009	-35.02%	**-9.98%**	-9.23%	**-14.82%**	-0.99%
July 2009 - June 2010	8.71%	**5.13%**	3.90%	**-1.08%**	0.77%
July 2010 - June 2011	33.76%	**14.88%**	6.78%	**10.69%**	1.41%
July 2011 - June 2012	-4.94%	**-3.53%**	-0.37%	**-2.27%**	1.23%
July 2012 - June 2013	11.91%	**-0.57%**	5.16%	**9.17%**	-1.85%
July 2013 - June 2014	26.50%	**6.61%**	6.47%	**11.95%**	1.46%

PORTFOLIO MANAGEMENT

Measuring the Performance of Private Infrastructure Debt

Frédéric Blanc-Brude
Research Director
EDHEC Risk Institute—Asia

Majid Hasan
Research Assistant
EDHEC Risk Institute—Asia

Estimating the performance of infrastructure debt instruments has become a recurring question for both long-term investors and prudential regulators. In a new paper (Blanc-Brude, Hasan, and Ismail, 2014)[34], we propose the first robust valuation, risk measurement and data collection framework for private infrastructure project loans.

We focus on those performance measures that are the most relevant to investors at the strategic asset allocation level, and to prudential regulators for the calibration of risk weightings, including expected loss, expected recovery rates, loss given default, value-at-risk (VaR), expected shortfall or CVaR, duration, yield and z-spread. We also determine parsimonious data collection requirements. Hence, we can realistically expect to deliver these performance measures at a minimal data collection cost.

Marking to business models

As for any security, the valuation of infrastructure project finance loans consists of modeling or observing cash flows and deriving their present value. However, cash-flow data for large, representative samples of projects and spanning their entire lifecycle are not yet available. It is one of the objectives of this article and of the Natixis research chair on infrastructure debt at EDHEC-Risk Institute to determine what data needs to be collected and to build a global database of infrastructure project debt metrics.

Until such a large dataset has been built, we must proceed in two steps: we first model the cash flows of generic but commonly found infrastructure project financing structures and calibrate these models with existing data, allowing for new calibrations when larger datasets become available. Second, given a generic cash flow model, we build a valuation model to derive the relevant return and risk measures. So we are effectively marking to a business model that reflects the available knowledge of private infrastructure project credit risk today.

This exercise also yields the list of data points that need to be collected to update and better calibrate this model and improve our knowledge of the performance of infrastructure debt.

We show that documenting the dynamics of the debt service cover ratio (DSCR) in infrastructure project finance vehicles, in combination with information about initial leverage, covenant triggers and the size of the loan's "tail" (i.e., the difference between the original loan maturity and the life of the project), is sufficient to derive key credit risk metrics in infrastructure project finance, including default frequencies and distance to default.

In particular, we show that knowledge of the statistical distribution of the DSCR in infrastructure projects is sufficient to predict default and compute distance to default measures, allowing the development and implementation of a powerful structural credit risk model à la Merton (1974).

In terms of data availability, we know that DSCRs are typically monitored and recorded by infrastructure creditors, while the base case debt service and other project characteristics are documented at financial close. Hence, the data that is required is observable.

Families of infrastructure debt financing

We focus on two families of financial structures, which correspond to a large number of real-world infrastructure projects and their associated debt securities: merchant infrastructure and contracted infrastructure.

Merchant infrastructure refers to those projects that generate revenue by selling their output or service in a market, and hence are exposed to commercial risks, while contracted infrastructure projects receive contracted revenue in exchange for providing a pre-agreed output or service, and bear little to no market risk.

Examples of merchant infrastructure projects include a power plant that sells electricity at market prices or a road collecting tolls from users. Examples of contracted projects may include schools and hospitals that receive a fixed payment from a government entity upon the satisfactory delivery and maintenance of an infrastructure, or an energy project financed on the back of a take-or-pay purchase agreement.

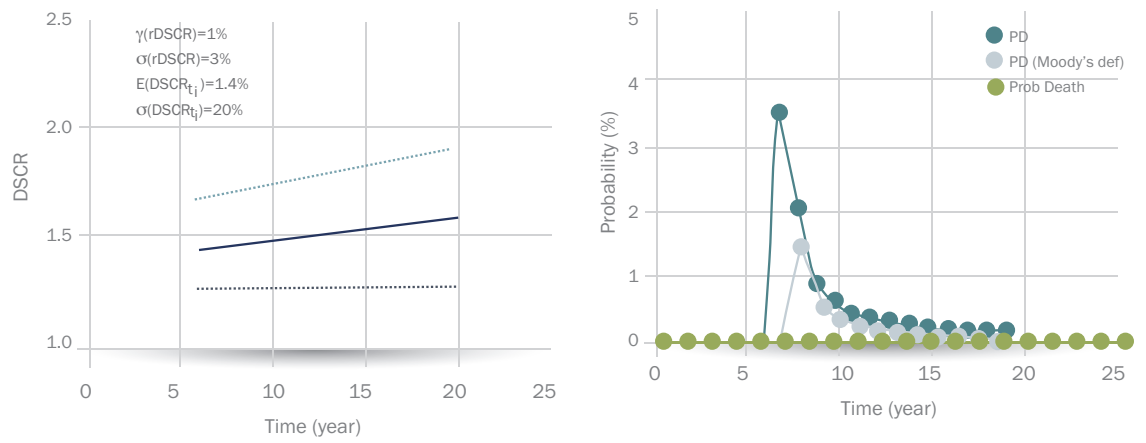
These two types of project structures correspond to different underlying business risks, and as a consequence, are structured in different ways. As illustrated in Exhibit 1, merchant infrastructure projects are structured with a rising mean DSCR and a longer tail. A rising DSCR implies that lenders get paid faster than equity owners, and a longer tail increases the value of lenders' security. In other words, lenders demand an increasing mean DSCR and a longer tail to protect themselves against higher and increasing cash-flow volatility, which results from higher revenue risk.

In contrast, contracted projects are structured with a flat DSCR and shorter tails, as lenders demand less protection against default due to lower expected underlying revenue risk.

Of course, other generic infrastructure project financing structures exist, even though they tend to be a combination of these two types — e.g., shadow toll roads collect a volume-based income paid typically by a government.

EXHIBIT 1

Rising debt service cover ratio profile and probability of default for a generic 25-year "merchant" infrastructure project with a 5-year construction period and a 7-year tail. Right-hand side: the dark green line (PD) indicates the probability of technical default, the gray line (Moody's definition) corresponds to the portability of hard default. The light green line is the probability of bankruptcy.



The value of the tail

Combined with the Base Case Debt Service, the distribution of the DSCR in generic projects can also be used to infer the expected value and volatility of the cash flow available for debt service (CFADS) of a typical infrastructure project.

However, the base case determined at financial close can change following a breach of covenant or a hard default, leading to the restructuring of the debt schedule and its extension in the loan's tail. To take into account these potential changes in the debt schedule and "value the tail," we model the debt renegotiation process to determine the outcome of restructuring after either a technical (covenant-driven) or a hard default (of payment). A new debt service is determined by taking into account what each party would lose in the absence of a workout.

Thus, we can determine the cash flows to infrastructure project creditors in every future state of the world. To value these cash flows, we take a so-called structural approach and develop a version of the Merton (1974) model that takes into account the characteristics of infrastructure project finance debt, and combine value of the debt service in different states by adapting the Black and Cox (1976) decomposition to the case of project finance workouts.

Key findings: a low but dynamic risk profile

For parameter estimates corresponding to current industry practices, we find that the debt of both types of generic infrastructure projects discussed, merchant and contracted, exhibit highly dynamic risk profiles. Our results show the importance of valuing the loan's tail to get an accurate picture of the risk profile of infrastructure project debt. Overall, we find that the different aspects of credit risk in infrastructure projects can largely be explained by their DSCR profiles, tail values and the costs of exit relative to the cost of renegotiation for lenders.

Using Moody's definition of default in project finance by which each loan is only allowed to default once (Moody's, 2014) our model predicts marginal default frequencies in line with reported empirical averages: trending downwards from just under 2% at the beginning of the loan's life to almost zero

[34] *Blanc-Brude, F., M. Hasan and O. R. H. Ismail. 2014. Unlisted Infrastructure Debt Performance Measurement. Natixis research chair on Infrastructure Debt Investment Solutions. Singapore: EDHEC-Risk Institute. This paper and the present article are drawn from the Natixis research chair at EDHEC-Risk Institute on the "Investment and Governance Characteristics of Infrastructure Debt Instruments."*

after 10 years, in the case of merchant infrastructure, and flat at 0.5% for contracted projects, i.e., public-private partnerships (see, for example, Moody's, 2014).

Overall, risk levels are found to be relatively low and recovery relatively high: expected loss (EL) never rises above 2%; VaR and CVaR, while they increase towards the end of the loan's life as the value of the tail is exhausted, never reach levels higher than 6% and 10%, respectively; and expected recovery rates are always in the 80% to 100% range.

In the case of merchant infrastructure projects, the probability of both technical and hard defaults (PD), and of hard defaults only (Moody's definition) shown in the top-left quadrant of Exhibit 2, goes down sharply post construction, while expected (EL) and extreme (VaR, CVaR) losses tend to rise throughout the loan's life. Similarly, in the case of contracted infrastructure projects, while PD stays almost constant during the loan's life, the severity of losses increases with time.

The diverging trends in the distribution of defaults and losses are a consequence of debt restructurings upon defaults. Even if defaults are concentrated in a certain period of time, debt restructuring spreads losses over the entire life of the project. Hence, losses tend to increase with time, as the cumulative number of defaults (and hence, restructurings) accrue losses near the end of the loan's life. However, part of the losses suffered during the loan's life is recovered in the loan's tail, thus reducing overall expected losses.

The size of losses for both DSCR families is primarily influenced by lenders' exit value net of exit costs. Exit costs determine the aggregate loss of value (debt plus equity) if the debt owners take over the project company upon a hard default and do not renegotiate with the original equity investors.

The higher the exit costs, the lower the value that lenders can obtain by taking over the project company after a hard default, and the lower their bargaining power in negotiations with original equity holders. Hence, lenders may have to suffer losses even in otherwise low risk projects like contracted infrastructure because replacing the equity owners upon a hard default, while it is in their power, can be very costly in some cases.

As a consequence, ongoing monitoring of the SPE conducted is required of lenders in the project in order to avoid ever having to contemplate exercising their option to exit, in particular, technical default triggers (e.g., a low DSCR or loan-life cover ratio) allow lenders to intervene and maximize their recovery rates long before more expensive options to restructure, sell or liquidate the SPE ever arise.

Finally, our approach also allows us to derive expected returns and yield measures and highlights the fact that the ability to reschedule debt upon technical and hard default creates a trade-off between credit risk and duration risk. That is, to reduce the credit losses upon default, investors have to extend the maturity of their loan further in the tail, and have to bear a higher interest rate risk due to a higher duration. This trade-off is shown in the bottom-right quadrant of Exhibit 2.

Next steps: data collection and portfolio construction

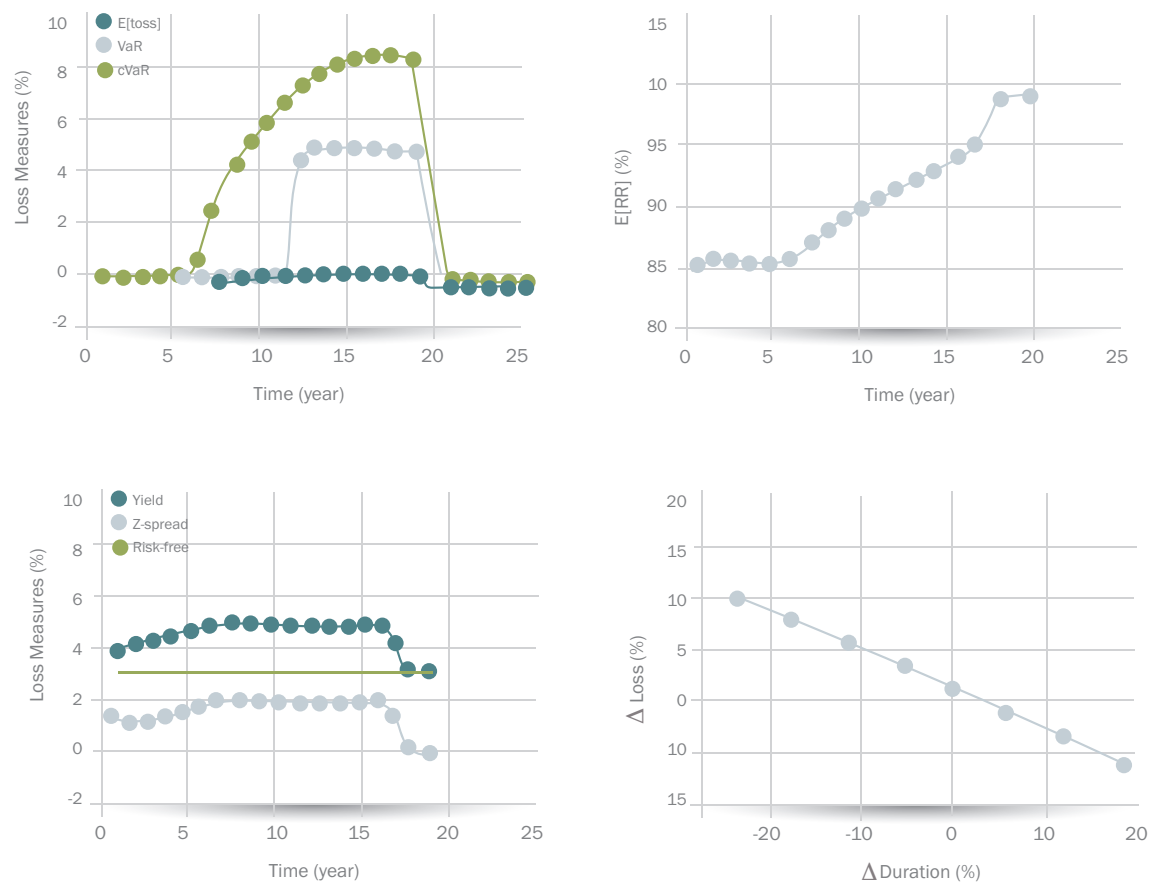
Thus, with a parsimonious set of inputs that consists of the parameters of the DSCR distribution across different types of generic projects, the base case debt schedule and a number of variables defined in the covenants at financial close, infrastructure project finance loans can be valued at any point in time, and their risk/return profile can be constructed spanning the entire life of the loan.

Our study delivers the first three steps of the roadmap defined in Blanc-Brude (2014) with respect to infrastructure debt investment: defining the most relevant underlying financial instrument, designing a valuation framework that is adapted to its private and illiquid nature, and the determination of a standard for data collection and investment performance reporting in infrastructure debt investment.

Next steps include active data collection to better calibrate our model of dynamics, before moving to the portfolio level of the analysis, towards long-term investment benchmark in infrastructure debt. •

EXHIBIT 2

Credit risk metrics for merchant infrastructure. Top-left quadrant: Expected and extreme loss measures at time t = 0; top-right quadrant: Expected recovery rate in time (conditional on no default until time t); bottom-left quadrant: Yield; bottom-right quadrant: Trade-off between duration and credit risk.



The research from which this article was drawn was produced as part of the Natixis "Investment and Governance Characteristics of Infrastructure Debt Instruments" research chair at EDHEC-Risk Institute.

PORTFOLIO MANAGEMENT

Constructing a Valuation Framework for Privately Held Infrastructure Equity Investments

Frédéric Blanc-Brude
Research Director
EDHEC Risk Institute—Asia

Majid Hasan
Research Assistant
EDHEC Risk Institute—Asia

In new research[35] drawn from the work of the Meridiam/Campbell Lutyens research chair at EDHEC-Risk Institute, we propose the first valuation framework dedicated to privately held infrastructure equity investments.

Following the roadmap to create long-term infrastructure investment benchmarks described in Blanc-Brude (2014), we develop a framework that takes into account the challenges of valuing privately held and seldom-traded infrastructure equity investments, with the aim of designing a methodology that can be readily applied given the current state of empirical knowledge and, going forward, at a minimum cost in terms of data collection.

Three challenges

The valuation of unlisted infrastructure project equity stakes requires three significant challenges to be addressed:

- Endemic data paucity: while primary and secondary market prices can be observed, sufficiently large and periodic samples, representative of different types of infrastructure projects at each point in their multi-decade lifecycle, are unlikely to be available every year in each regional market.
- The term structure of expected returns: the nature of such investments requires the estimation of a term structure of discount factors at different points in their lives that reflects the change in their risk profile. Indeed, in expectation, infrastructure investments can exhibit a dynamic risk profile determined by the sequential resolution of uncertainty, the frequent de-leveraging of the project company's balance sheet or the existence of a fixed-term to the investment, which creates a time-varying duration.
- The absence of a unique price for a given investment in unlisted infrastructure, which springs from the fact that there is no traded equivalent to the payoff of infrastructure project equity. It follows that prices are partly driven by investor preferences and that substantial bid/ask spreads are likely.

The first point is partly a mundane aspect of the difficulties encountered when collecting data on private investments, but also a reflection of the nature of long-term equity investment in infrastructure. Indeed, the type of infrastructure projects that have been financed in the past are not necessarily representative of investment opportunities today. Thus, even if year-23 dividends for projects that were financed 24 years ago can be observed today, they may not be good predictors of dividends in projects financed three years ago, 20 years from now. For example, projects financed in the early 1990s may have been in sectors where fewer projects exist today (e.g., telecoms) or rely on contractual structures or technologies that are not relevant to long-term investors in infrastructure today (e.g., coal-fired merchant power).

If data paucity is an endemic dimension of the valuation of privately held infrastructure equity investments, we must start from the premise that we cannot observe enough data to simply derive prices empirically. Instead, we acknowledge a position of relative ignorance and aim to build the possibility of improving our knowledge into our approach as new observations that can be used to update models of dividend distributions become available.

The second point about the term structure of expected returns has long been made in the finance literature: using such constant and deterministic discount rates is defective if projects have multiple phases and project risk changes over time as real-options are exercised by asset owners.

It also amounts to assuming that the risk-free rate, asset beta and market risk premium are constant and deterministic, when we know that such variables are time-varying and stochastic. Moreover, the internal rate of return (IRR) of individual investments cannot be easily used to estimate performance at the portfolio level, as the IRR of a portfolio is not the same as the weighted average IRRs of individual investments.

Thus, using methodologies based on discounting at a constant rate, while common in the corporate sector, is inadequate for the purposes of long-term investors who need performance measures that can help them make hedging, risk management and portfolio management decisions.

The third point (the absence of unique pricing measures) is a reflection of what is usually labelled "incomplete markets," i.e., the fact that the same asset can be valued differently by two investors, and yet this does not constitute an arbitrage opportunity (and therefore the bid-ask spread does not narrow) because transaction costs are high and because in the absence of complete markets, investors' heterogeneous preferences partly explain prices.

The existence of a range of (or bounds on) values is also impacted by market dynamics: if a new type of investor (e.g., less risk averse) enters the private infrastructure equity market, the range of observable valuations for similar assets may change. Likewise, if some investors want to increase their allocations to unlisted assets, given the limited available stock of investible infrastructure projects at a given point in time, their valuations may rise, but not that of others (who may sell).

Hence, the important point that the required rate of return or discount rate of individual investors' infrastructure equity is fundamentally unobservable: it cannot be inferred from observable transaction prices since it is both a function of the characteristics of the asset (e.g., cash-flow volatility) and individual investor preferences.

Existing approaches are inadequate

Because of these challenges, existing approaches developed to value private-equity investments are mostly inadequate for the purpose of valuing unlisted infrastructure project equity.

In our review of the literature, we identify three groups of valuation techniques: repeat sales, public market equivalents and factor extraction from cash flows. Importantly, these techniques all imply that enough data can be observed to compute a price.

The repeat sales approach assumes that asset betas can be inferred from discrete and unevenly timed transaction observations after correcting for price staleness and sampling bias, while the public market equivalent approach implies that public asset betas can be combined to proxy the return of unlisted assets. Cash flow-driven approaches are less normative and aim to derive the unobservable rate of return of unlisted assets by decomposing their implied returns into traded and untraded components ex post facto, that is, once all cash flows have been observed and can be related to equally observable market factors.

[35] *Blanc-Brude, F. and M. Hasan. 2015. The Valuation of Privately-Held Infrastructure Equity Investment. Meridiam/Campbell Lutyens research chair at EDHEC-Risk Institute on Infrastructure Equity Benchmarking. Singapore: EDHEC-Risk Institute, March.*

Thus, these approaches cannot be directly applied to privately held infrastructure investments, the value of which is determined by streams of expected and risky cash flows that mostly occur in the future, and for which few comparable realized investments exist today.

Existing approaches also typically fail to take into account the subjective dimension of asset pricing in the unlisted space and compute asset betas and alphas as if a unique pricing measure existed, that is, as if all investors had similar preferences, and in some papers, as if private equity exposures could always be replicated with a combination of traded assets.

Endogenously determined discount factors

To the extent that infrastructure dividend cash flows can only be partially observed today, their expected values cannot be decomposed into exogenous factors (markets, the economy, etc.), the future value of which is not known today and would be very perilous to predict thirty years from now.

Instead, we must derive the relevant discount factors endogenously, that is, using observable information about each private investment in infrastructure equity including, as suggested above, its contractual characteristics, location, financial structure, etc., as well as the value of the initial equity investment made, which is also observable.

Hence, we argue that a robust valuation framework for equity investments that solely create rights to future (and yet largely unobserved) risky cash flows, as is the case of privately held infrastructure equity, requires two components:

1. A model of expected dividends and conditional dividend volatility, calibrated to the best of our current knowledge;
2. A model of endogenously determined discount factors, that is, the combination of expected returns implied by the distribution of future dividends, given observable investment values.

In other words, as for any other stock, the valuation of privately held equity in infrastructure projects amounts to deriving the appropriate discount rates for a given estimate of future dividends. But while this process is implicit in the pricing mechanism of public stock markets, in the case of privately held equity with distant payoffs, we have to derive the relevant parameters explicitly, taking into account the characteristics of infrastructure assets.

Dividend distribution model & required data

The dividend stream or cash flow process can be described as "state-dependent" and we introduce a new metric for infrastructure project dividends — the equity service cover ratio, or ESCR, which is computed as the ratio of realised-to-base case dividends.

The base case equity forecast of infrastructure equity investments, while not necessarily accurate, provides a useful and observable quantity, which by definition spans the entire life of each investment. Thus, we propose to describe the behavior of equity cash flows in infrastructure projects as a function of this initial forecast, in order to create metrics allowing direct comparisons between different equity investments.

In our research, we show that the value of the ESCR at each point in the lifecycle of infrastructure equity investments can be used as a state variable describing the dynamics of the cash-flow process. In combination with a given project's base case dividend forecast (which is known at the time of investment), knowledge of the distribution of the ESCR at each point in time is sufficient to express the expected value and conditional volatility of dividends.

The fact that new observations are not redundant today (we can still learn about the dynamics of dividends in infrastructure investment by collecting new data) justifies the need for an ongoing and standardized reporting of these cash flows to keep learning about their true distribution and value the infrastructure investments made today, tomorrow.

Filtering implied market values (and their bounds)

Since the term structure of expected returns of individual investors/deals is unobservable and lies within a range (or bounds) embodying market dynamics at a given point in time, we adapt the classic state-space model mostly used in

EXHIBIT 1

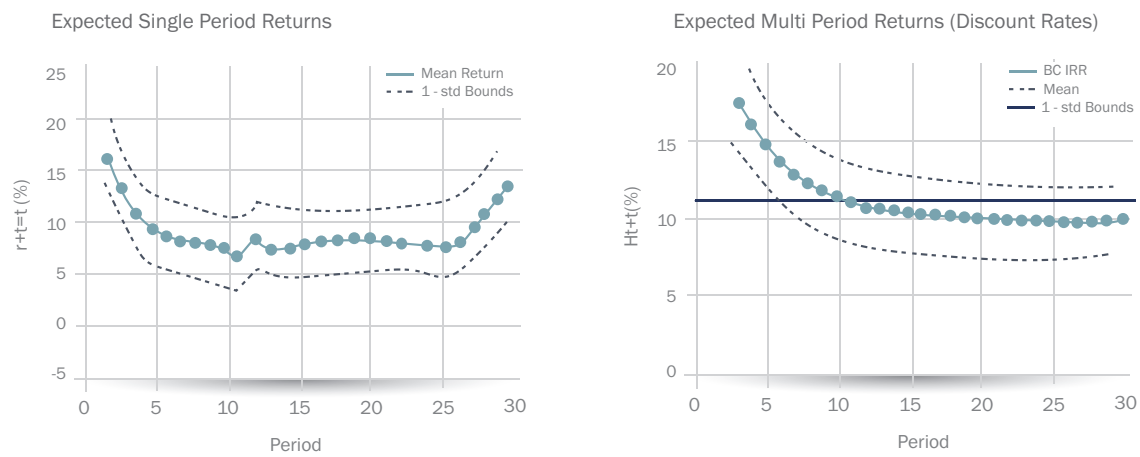


EXHIBIT 2

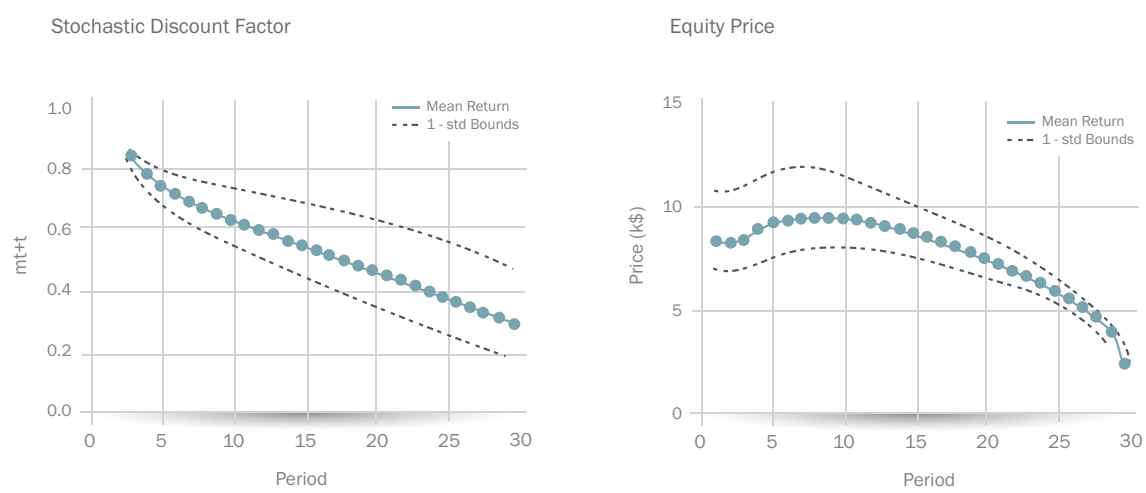
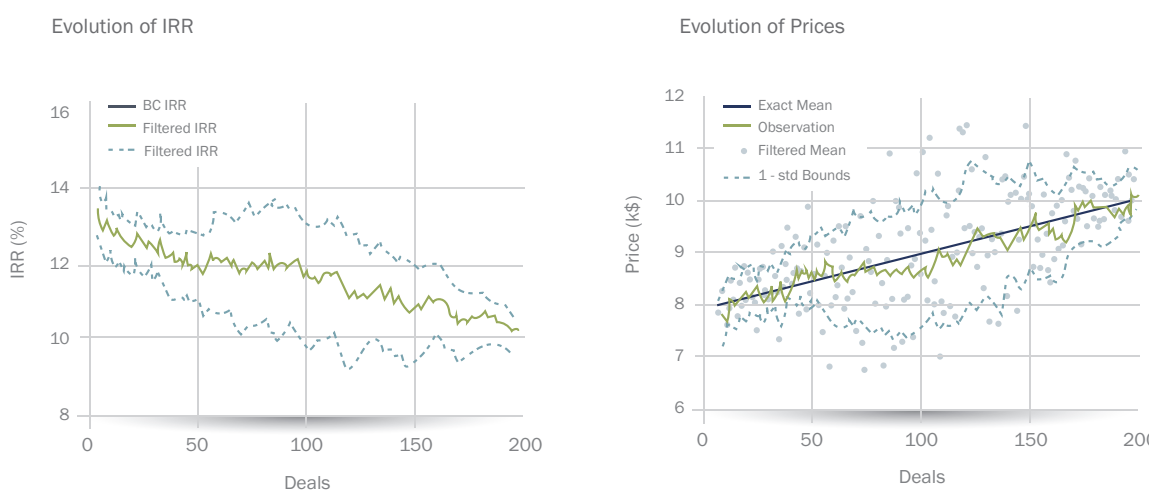


EXHIBIT 3



physical and natural sciences to capture the implied average valuation (or state) of the privately held infrastructure equity market at one point in time and its change from period to period. Using such a model also allows us to capture the market bounds on value implied by observable investment decisions for a given stream of expected cash flows.

The objective of state-space models is parameter estimation and inference about unobservable variables in dynamic systems, that is, to capture the dynamics of observable data in terms of an unobserved vector, here the term structure of discount factor. Hence, we have an "observation equation" relating observable data to a state vector of discount factors, and a "state equation," which describes the dynamics of this state, from one observation (transaction) to the next. Each transaction corresponds to a new state, i.e., a given term structure of discount factors matching the price paid in that transaction (the initial investment) with expected cash flows, which may or may not be the same as the previous transaction's.

Given a stream of risky future dividends, if the price paid in the current transaction is different from that paid in the previous one, it must be because the valuation state has shifted. The valuation state can change due to a change in investor preferences between the two deals, or due to a change in the consensus risk profile of that kind of investment (e.g., projects with commercial revenues after a recession), or because of a change in the overall market sentiment (the average) valuation.

Thus, by iterating through transactions, we may derive an implied average valuation state (a term structure of discount factors) and its range, bounded by the highest and lowest bidders in the relevant period.

Later, when dividend payments are realized, period returns can be computed using the discounted sum of remaining cash flows as the end-of-period value (given the implied term structure of discount factors at that point).

In our research, we define the observation equation using a dynamic version of the standard Gordon growth model (discounted dividends) and the state equation using an autoregressive model of the term structure of expected returns which can be derived from the kind of factor models of expected excess returns that are commonly found in the literature. We take the view that expected returns are a function of conditional dividend volatility.

In a simple, linear setting, we show that we can iterate through observable investments, while estimating model parameters on a rolling basis, to capture both the implied expected returns (and discount factors) during a given reporting period and track these values and their range (arbitrage bounds) from period to period.

Illustration

As an illustration of our approach, we apply the dividend and pricing models to a generic case of privately held infrastructure investment, assuming an expected ESCR and ESCR volatility profile (including the probability of receiving no dividends in any given period).

Given a base case dividend scenario inspired by an actual infrastructure project financed in Europe in the last decade, we obtain a full distribution of future dividends and apply our valuation framework to this assumed dividend process for a (or an equally assumed) range of investment values. Some of the key outputs are shown in the following figures.

Exhibit 1 shows the resulting filtered term structure of expected period and multi-period (average) expected returns filtered from a range of 20 initial transactions.

Exhibit 2 shows the resulting values of the dividend discount factor[36] at the time of valuation and the expected average price and its range for this group of transactions.

Finally, figure 3 shows how we can implement this model with rolling parameter estimation to track the implied average expected returns and price of consecutive transactions from period to period[37].

These results spring from model inputs that are only inspired by existing data and a number of intuitions about privately held infrastructure equity investments, and can only be considered an illustration. However, they show clearly that with well-calibrated cash-flow models and a transparent valuation framework, the kind of performance measures that have so far been unavailable to long-term investors can readily be derived and monitored over time, as new investments are made.

Future steps

Next steps include the implementation of our data collection template to create a reporting standard for long-term investors and the ongoing collection of said data. Beyond, in future research, we propose to develop models of return correlations for unlisted infrastructure assets in order to work toward building portfolios of privately held infrastructure equity investments. These developments will take place with the support of, and in collaboration with, the financial industry and its regulators. •

The research from which this article was drawn was produced as part of the Meridiam/Campbell-Lutyens "Infrastructure Equity Investment Management and Benchmarking" research chair at EDHEC-Risk Institute.

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[36] *Using continuously compounded (log) returns, the discount factor is simply the exponent of minus the total return from the valuation date until the relevant period.*

[37] *In this example, the average price investors are willing to pay for the same infrastructure asset is assumed to increase continuously (perhaps because investors increasingly value assets that pay predictable dividends in bad states of the world) but the range of prices investors are willing to pay to buy a stake in this (unchanged) dividend process is also assumed to change. Initially it is assumed to widen (say that new investors become active in this market and have different preferences or views on risk); half way through the 200 observed transactions, the range of valuations is assumed to start shrinking (perhaps there is now a greater consensus amongst investors about risk or more traded assets allowing replication).*

PORTFOLIO MANAGEMENT

Funds of Hedge Funds: In Search of The X-Factor

Mathieu Vaissié
Research Associate
EDHEC-Risk Institute; Partner, Ginjer AM

The Long/Short Equity fund launched by Alfred W. Jones in 1949 is often referred to as being the very first hedge fund (HF). But it was only five decades later, in the wake of the bursting of the TMT bubble, that HFs entered the mainstream. It is indeed with the massive arrival of institutional investors that they came into the light. Starting in the early 2000s, HFs have seen their assets under management boom, which fostered the launch of thousands of new funds. HFs could use leverage, go long and/or short, they could gain exposure to a wide array of instruments; they were very different animals. And they naturally attracted a lot of attention. This is all the more true in that they were very secretive and disclosed very little information about their activities. Many studies were thus published then to try to better understand the genuine risk/return properties of HFs, and in turn, to tackle the crucial issue of the fund selection process. But picking the right managers within a barely observable universe made up of 8,000-plus funds is like finding a needle in a haystack. Not to mention the operational risks typically associated with HF investments.

Many institutional investors therefore made their first foray into alternative investment strategies through funds of hedge funds (FoHFs) that showed the appropriate skill sets and resources. FoHFs jumped on the bandwagon and saw their assets under management, and in turn, their number, explode as well in the middle of the 2000s. The subprime crisis and the subsequent systemic crisis put an end to the party to a certain extent. While high-net-worth individuals had historically been focused on the return dimension, institutional investors' primary concern is on the risk dimension. And, above and beyond disappointing performance, it is the capacity of FoHF managers to control risk properly that has been questioned throughout the crisis. It has become clear since 2008 that spreading capital across a selection of HFs is not enough to mitigate risk. Diversification is not about quantity, it is all about quality. The task is particularly challenging in the alternative arena in that HFs are managed actively and on a discretionary basis. The aggregated risk factor exposures of a selection of HFs are therefore liable to be in constant evolution. In an attempt to reinvent themselves and enhance their attractiveness, FoHFs are thus progressively moving away from the historical business model of mere gate keepers, giving access to a short list of managers, and they are striving to morph into networks of expertise (e.g., allocation, fund selection, portfolio construction, etc.), organized around the risk management function. "Solutions" is the new buzzword. Here again, picking the right manager within a very disparate universe made up of 2000 FoHFs or so is anything but straightforward. And, quite surprisingly, even if FoHFs remain a venue of choice for institutional investors, the FoHF selection problem has attracted very little attention so far in the academic literature. In an attempt to fill this gap, we introduced a "pseudo" risk factor in Darolles and Vaissié (2014) making it possible to measure the capacity of a FoHF manager to manage risk efficiently. We call this pseudo risk factor the X-Factor.

The underlying intuition is very simple. Investors, especially institutional ones, are looking for managers who can make optimal use of the available information and adjust their portfolio dynamically, so that they can remain well adapted to an ever-changing environment, and in turn, minimize the level of (downside) risk for a given level of performance. Most FoHF managers claim to do so. In order to reduce the dimension of the FoHF selection problem, and identify those who actually do, we propose a new tactical style allocation factor — the X-Factor — that is designed with the objective of capturing the benefits of such active risk management. The higher the FoHF's sensitivity to this new factor, the higher the manager's capacity to capture the upside potential while controlling for (downside) risk.

From a technical perspective, we leverage on the regime switching dynamic correlation approach introduced in Pelletier (2006) and adapted by Giamouridis and Vrontos (2007) to the context of HF portfolios to build the X-Factor. By doing so, we can take into account the dynamics of both the variance and the correlation matrices, and build a portfolio that remains optimally diversified through time. Of note, in order to isolate the benefits of active risk management, we focus on the one portfolio on the efficient frontier for which no information on expected returns is required — that is, the portfolio with the minimum amount of risk. Moreover, in order to ensure the investibility of the X-Factor, we use as underlyings a series of HF strategy indexes exclusively made up of managed accounts providing weekly liquidity (please refer to www.lyxor.com for more details on these indexes).

Once we have built the X-Factor, we can decompose the performance of a FoHF into three components: one, the market component, two, the return derived from active management of the underlying risk factor exposures (i.e., at the strategic allocation, tactical allocation and/or fund selection levels), and three, the outperformance stemming from idiosyncratic risks (i.e., the alpha). We therefore obtain the following regression equation:

$$R_i = \alpha_i + \beta_i \overbrace{R_{MKT}}^{\text{Market Risk}} + \gamma_i \overbrace{(R_X - R_{MKT})}^{\text{X- Factor}} + \varepsilon$$

Where Ri denotes the return of the FoHF i, RMKT the return of the Lyxor composite index, and RX the performance of the X-Factor. The error term ε is assumed to be independently identically distributed (i.i.d.) zero-mean white noise.

Put differently, we propose to augment the CAPM with the X-Factor, which simply consists of the outperformance generated by a FoHF manager managing his aggregated risk factor exposures efficiently. Our approach is in this respect close to the model proposed by Henriksson and Merton (1981). The main difference is that we are in a multi-factor setting and consider a skilled FoHF manager to be one who is good at dealing with the instability of the variance/co-variance matrix, as opposed to capturing the ups and downs of the market. A diversified HF portfolio is indeed exposed to a wide range of systematic risk factors, and the key goal of the portfolio manager is not to time each and every factor, but to ensure that the portfolio remains properly diversified through time. To this end, he/she must mitigate the impact of the instability of the risk structure by actively adjusting the underlying aggregated risk factor exposures. The higher the factor loading γ_i the greater his or her capacity to do so.

For the sake of illustration, we carried out a regression analysis on the database provided by Morningstar, from January 2005 through December 2012. We only considered FoHFs denominated in US$, showing a minimum of $5 million in assets under management, and with a continuous track record over the whole observation period. Finally, in an attempt to mitigate the double-counting issue, we identified the FoHFs with a similar name showing a correlation greater than or equal to 0.95, and we only kept the one with the longest track record and/or the institutional share class when a distribution share class was also available. We therefore ended up with a sample of 262 FoHFs with 96 months of continuous return streams.

In order to assess the impact of the X-Factor, we ranked all the FoHFs based on their factor loading γ_i, and formed five quintiles made up of approximately 50 FoHFs each. The first observation, as one could have expected, was that the group of FoHFs showing the highest exposures to the X-Factor tend to be associated with greater liquidity (i.e., higher redemption frequency together with lower notice period). The second observation was that these FoHFs tend to lag their peers during strong bull markets, but they stand out from the crowd and post substantial excess returns relative to their peers as soon as market conditions become more unstable. In other words, they are implicitly long an option on the (in)stability of the underlying risk structure of the market: there is a little premium to pay when market conditions are stable, but it pays off a lot more as soon as uncertainty arises. It follows that FoHFs with a high exposure to the X-Factor turn out to do materially better over the long run. Unfortunately, many are called, but very few are chosen. Only 20 FoHFs out of 262, i.e., 8% of the population, exhibit a positive loading to the X-Factor. The good news, though, is that we find significant persistence in both the highest and the lowest loadings to the X-Factor (i.e., the probability of one FoHF remaining in the same quintile from one year to the next is 70% and 68%, respectively), suggesting that investors can leverage on our pseudo risk factor to separate the wheat from the chaff.

With over $3 trillion in assets under management, the HF industry is at a historical high. And yet, the decision recently made by very large, high-profile institutional investors to cut their HF programs, because of their high costs and complexity, launched a debate on their actual benefits. FoHFs add an extra layer of fees, and they will bring additional complexity as they turn themselves into manufacturers of customized solutions. Chances are therefore high that FoHFs will be under greater scrutiny going forward. In this respect, the X-Factor provides investors with a pragmatic yet robust approach to assessing the extent to which they are likely to get value for their money, and in turn, to solve the FoHF selection problem. •

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