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Introduction

Noël Amenc

It is my pleasure to introduce the latest issue of the EDHEC Research Insights supplement to IPE, which aims to provide European institutional investors with an academic research perspective on the most relevant issues in the industry today.

Multi-factor models are standard tools for analysing the performance and the risk of equity portfolios. In addition to analysing the impact of common factors, equity portfolio managers are also interested in analysing the role of stock-specific attributes in explaining differences in risk and performance across assets and portfolios. In our article, produced as part of the CACEIS New Frontiers in Risk Assessment and Performance Reporting research chair at EDHEC-Risk Institute, we explore a novel approach to address the challenge raised by the standard investment practice of treating attributes as factors, with respect to how to perform a consistent risk and performance analysis for equity portfolios across multiple dimensions that incorporate micro attributes.

A number of index providers have launched new forms of alternative indices to try to address some of the challenges with traditional weighting schemes based on the market value of debt. A number of ad-hoc alternative weighting schemes have been proposed but these initiatives have no academic grounding, and it is unclear whether the portfolios thus constructed would be optimal benchmarks under any reasonable assumptions. In our article, we provide a broad overview of these initiatives, which can be broadly classified into two different categories – fundamental approaches and diversification approaches. Our main conclusion is that none of these approaches successfully addresses all the key concerns and challenges involved in designing a truly investor-friendly bond benchmark, which suggests that further work is needed in the area of bond benchmarks.

The focus of smart beta strategies has recently shifted to encompass the fixed income asset class. We put the search for factors and beta strategies in the context of asset pricing, and we show that compensation for non-market factors is not just allowed, but actually required, by financial theory.

In an article drawn from the FBF Innovations and Regulations in Investment Banking research chair at EDHEC-Risk Institute, we provide an overview and analysis of the framework used by large financial institutions to determine initial margin and variation margin payments when trading non-cleared over-the-counter derivatives. This new framework, which came into effect in September 2016, is based on the recommendations of the BCBS/IOSCO Working Group on Margin Requirements.

The results of our research on smart beta replication costs provide an explicit estimate of costs applied to a range of strategies and show the impact of using different implementation rules or stock universes. Importantly, given the transparent methodology and benign data needs, our replication cost analysis

is straightforward and can be easily applied to other strategies. This research was produced as part of the Amundi ETF, Indexing & Smart Beta ETF and Passive Investment Strategies research chair at EDHEC-Risk Institute.

In research supported by BdF Gestion, we examine the argument that portfolio rebalancing, defined as the simple act of resetting portfolio weights back to the original weights, can be a source of additional performance. Our analysis on individual stocks' characteristics highlights that size, value, momentum and volatility are sorting characteristics which have a significant out-of-sample impact on the rebalancing premium.

We introduce a new ERI Scientific Beta approach with the objective of maximising exposure to the long-term rewarded equity factors in a 'top-down' framework, in a robust and well-diversified manner. Scientific Beta's Multi-Beta Diversified Max Factor Exposure index dynamically allocates across single-factor indices in order to retain diversification benefits and obtain maximum exposure while maintaining balance across factors and reasonable diversification levels.

We examine the respective merits of the 'top-down' and 'bottom-up' approaches to multi-factor portfolio construction. 'Top-down' approaches assemble multi-factor portfolios by combining distinct sleeves for each factor, while the 'bottom-up' methods build multi-factor portfolios in a single pass by choosing and/or weighting securities by a composite measure of multi-factor exposures. We find that focusing solely on increasing factor intensity leads to inefficiency in capturing factor premia, as exposure to unrewarded risks more than offsets the benefits of increased factor scores.

We present the results of the first in-depth survey of institutional investors' perceptions and expectations of infrastructure investment. It documents the reasons for investing in infrastructure and whether currently available investment products or strategies are helping investors meet these objectives. The findings provide a first step towards integrating infrastructure in long-term investment solutions. Key findings are reported in the following areas: investment beliefs; products and objectives; benchmarking; and ESG (environmental, social and governance).

We ask whether focusing on listed infrastructure stocks creates diversification benefits previously unavailable to large investors that are already active in public markets. We conclude that what is typically referred to as listed infrastructure is not an asset class or a unique combination of market factors, but instead cannot be persistently distinguished from existing exposures in investors' portfolios.

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 IPE for their collaboration on the supplement.
Noël Amenc, Professor of Finance, EDHEC-Risk Institute, CEO, ERI Scientific Beta

Contents

Multi-dimensional risk and performance analysis for equity portfolios <i>Kevin Giron, Lionel Martellini, Vincent Milhau</i>	2
New frontiers in smart beta investing: benefits and limits of traditional and alternative bond benchmarks <i>Lionel Martellini</i>	5
Smart beta strategies in fixed income <i>Riccardo Rebonato</i>	7
Initial margin for non-centrally cleared OTC derivatives: overview, modelling and calibration <i>Dominic O'Kane</i>	11
Smart beta replication costs <i>Mikheil Esakia, Felix Goltz, Siva Sivasubramanian, Jakub Ulahel</i>	14
Measuring volatility pumping benefits in equity markets <i>Jean-Michel Maeso, Lionel Martellini</i>	17
Introducing a multi-beta diversified max factor exposure strategy <i>Felix Goltz</i>	21
Improving multi-factor exposure without sacrificing diversification and risk control <i>Felix Goltz</i>	24
Towards better infrastructure investment products? <i>Frédéric Blanc-Brude, Grace Chen, Tim Whittaker</i>	29
Looking for a listed infrastructure asset class <i>Frédéric Blanc-Brude, Tim Whittaker, Simon Wilde</i>	33



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Multi-dimensional risk and performance analysis for equity portfolios

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Attributes should remain attributes

Factor models, supported by equilibrium arguments (Merton [1973]) or arbitrage arguments (Ross [1976]), are not the only key cornerstones of asset pricing theory (APT). In investment practice, multi-factor models have also become standard tools for the analysis of the risk and performance of equity portfolios. On the performance side, they allow investors and asset managers to disentangle abnormal return (or alpha) from the return explained by exposure to common rewarded risk factors. On the risk side, factor models allow us to distinguish between specific risk and systematic risk, and this decomposition can be applied to both absolute risk (volatility) and relative risk (tracking error with respect to a given benchmark).

In addition to analysing the impact of common factors, equity portfolio managers are also interested in analysing the role of stock-specific attributes in explaining differences in risk and performance across assets and portfolios. For example, it has been documented that small stocks tend to outperform large stocks (Banz [1981]) and that value stocks earn higher average returns than growth stocks (Fama and French [1992]). Moreover, stocks that have performed best over the past three to 12 months tend to outperform the past losers over the next three to 12 months (Jegadeesh and Titman [1993]).

A common explanation for these effects, which cannot be explained by Sharpe's (1964) single-factor capital asset pricing model or CAPM (Fama and French [1993, 2006]), is that the size and the value premia are rewards for exposure to systematic sources of risk that are not captured by the market factor. This is the motivation for the introduction of the size and value factors by Fama and French (1993) as proxies for some unobservable underlying economic factors, perhaps related to a distressed factor. In this process, market capitalisation and the book-to-market ratio are used as criteria to sort stocks and to form long/short portfolios with positive long-term performance. In other words, what is intrinsically an attribute is turned into a factor. A similar approach is also used by Carhart (1997), who introduces a 'winners minus losers' factor, also known as the momentum factor.

More recently, investment and profitability factors have been introduced, so as to capture the investment and profitability effects: again Fama and French (2015) turn attributes into

- ➔ In investment practice, multi-factor models have become standard tools for the analysis of the risk and performance of equity portfolios.
- ➔ Equity portfolio managers are also interested in analysing the role of stock-specific attributes in explaining differences in risk and performance across assets and portfolios.
- ➔ We explore a novel approach to address the challenge raised by the standard investment practice of treating attributes as factors, with respect to how to perform a consistent risk and performance analysis for equity portfolios across multiple dimensions that incorporate micro attributes.
- ➔ Our research suggests a meaningful new dynamic approach, which consists in treating attributes of stocks as instrumental variables to estimate betas with respect to risk factors for explaining notably the cross-section of expected returns.

factors by sorting stocks on operating profit or the growth on total assets, while Hou, Xue and Zhang (2015) replace the former measure by the return on equity when constructing their profitability factor.

Overall, the standard practice of treating attributes as factors severely, and somewhat artificially, increases the number of factors to consider, especially in the case of discrete attributes. This raises a serious challenge with respect to how to perform a consistent risk and performance analysis for equity portfolios across multiple dimensions that incorporate both macro factors and micro attributes.

In this article, we explore a novel approach to address this challenge. As opposed to artificially adding new factors to account for differences in expected returns for stocks with different attributes, we seek to maintain a parsimonious factor model and treat attributes as auxiliary variables to estimate the betas with respect to true underlying risk factors. In other words, our goal is to decompose market exposure (beta) and risk-adjusted performance (alpha) in a forward-looking way as a function of the firm's characteristics, so that the attributes can remain attributes in the context of a parsimonious factor model, as opposed to being artificially treated as additional factors.

Our approach is somewhat related to the literature on conditional asset pricing models (Jagannathan and Wang [1996]), who also

allow the factor exposure to be a function of some state variables. One key difference is that standard conditional versions of the CAPM (eg. Ferson and Schadt [1996]), stipulate that betas (and possibly alphas and risk premia) are functions of underlying macroeconomic factors such as the T-Bill rate, dividend yield, slope of the term structure, credit spread, etc. In contrast, we take betas to be functions of the time-varying micro attributes or characteristics of the underlying firms that are typically used to define additional factors, including in particular market capitalisation, the book-to-market ratio and past one-year performance. Of course, one could in principle regard the factor exposures as a function of stock-specific attributes and pervasive state variables.

In what follows, we introduce a formal framework for estimating these so-called fundamental betas, as opposed to historical betas, and we provide evidence of the usefulness of these fundamental betas for (i) parsimoniously embedding the sector dimension in multi-factor portfolio risk and performance analysis, (ii) building equity portfolios with controlled target factor exposure, and also (iii) explaining the cross-section of expected returns.

Fundamental betas as functions of attributes

The traditional approach to measuring the market exposure of a stock or a portfolio is to run a time-series regression of the stock (excess) returns on a market factor over a rolling window. If the joint distribution of stock and market returns were constant over time, the sample beta at date $t-1$ would be a consistent estimator of the conditional beta on this date, and the variation in rolling-window estimates would be due to sampling errors only. Factor exposures, however, are not constant over time and the key challenge is therefore to estimate the beta for each stock conditional on the information available to date:

$$\beta_{i,t-1} = \frac{\text{Cov}[R_{i,t}, R_{m,t} | \Phi_{t-1}]}{\text{Var}[R_{m,t} | \Phi_{t-1}]}$$

where $R_{i,t}$ denotes the return on stock i in period $[t-1, t]$ in excess of the risk-free rate, $R_{m,t}$ is the excess return on the market portfolio and Φ_{t-1} is the information set available at date $t-1$. The traditional measure of conditional market exposure is the beta estimated over a sample period, but if the distributions of stock and market returns change over time, the sample estimates are not good estimators of the true

conditional moments. By shifting the sample period (rolling-window estimation), one does generate time dependency in the beta, but the 'historical beta' changes relatively slowly due to the overlap between estimation windows.

We introduce an alternative estimator for the conditional beta, which we name 'fundamental beta' because it is defined as a function of the stock's characteristics. More specifically, we first consider the following one-factor model for stock returns, in which the alpha and the beta are functions of the three observable attributes that define the Fama-French-Carhart factors: market capitalisation ($Cap_{i,t}$), the book-to-market ratio ($Bmk_{i,t}$) and past one-year return ($Ret_{i,t}$) for the stock i at date t . Hence we have the following relations:

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t} \times R_{m,t} + \varepsilon_{i,t}$$

$$\alpha_{i,t} = \theta_{\alpha,0,i} + \theta_{\alpha,Cap,i} \times Cap_{i,t} + \theta_{\alpha,Bmk,i} \times Bmk_{i,t} + \theta_{\alpha,Ret,i} \times Ret_{i,t}$$

$$\beta_{i,t} = \theta_{\beta,0,i} + \theta_{\beta,Cap,i} \times Cap_{i,t} + \theta_{\beta,Bmk,i} \times Bmk_{i,t} + \theta_{\beta,Ret,i} \times Ret_{i,t}$$

For N stocks, the model involves $8N$ parameters θ which tie the alphas and betas to the underlying stock characteristics. These parameters are estimated by minimising the sum of squared residuals over all dates and stocks in a procedure known as pooled regression.

Because the coefficients are independent from one stock to the other, the pooled regression is actually equivalent to N time-series regressions:

minimise $\sum_{i,t} \varepsilon_{i,t}^2$ is equivalent
to minimise $\sum_t \varepsilon_{i,t}^2$ for each i

Hence, the coefficients can be estimated separately for each stock, by running a time-series regression. More specifically, we regress each stock's excess return on the market return and the market return crossed with the stock's attributes. For a stock i , the regression equation takes the form:

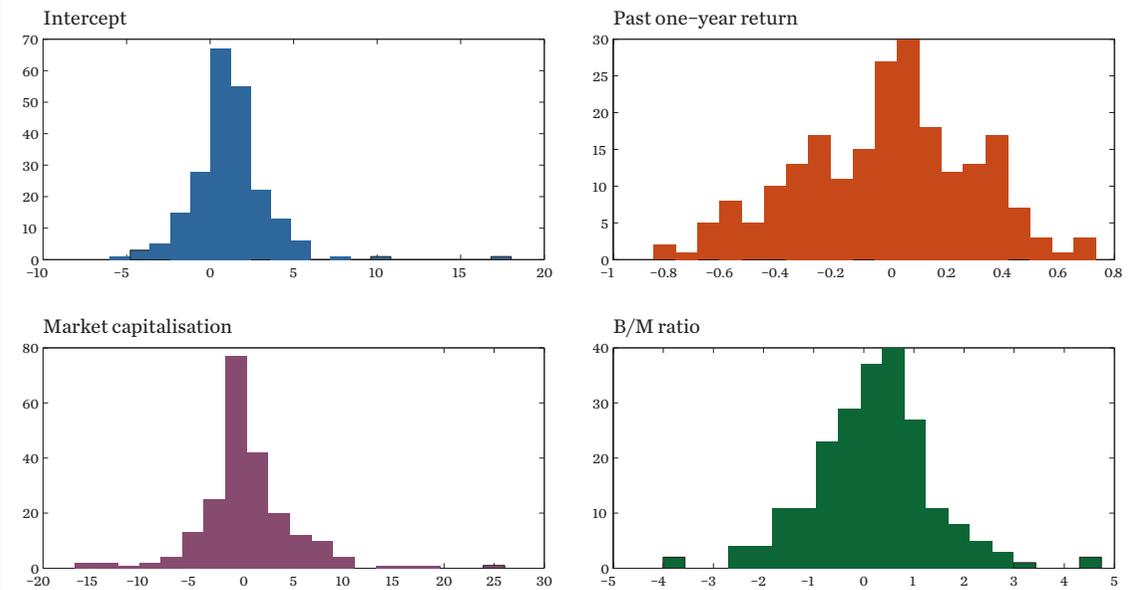
$$R_{i,t} = \theta_{\alpha,0,i} + \theta_{\alpha,Cap,i} \times (Cap_{i,t}) + \theta_{\alpha,Bmk,i} \times Bmk_{i,t} + \theta_{\alpha,Ret,i} \times (Ret_{i,t}) + \theta_{\beta,0,i} \times R_{m,t} + [\theta_{\beta,Cap,i} \times (Cap_{i,t}) + \theta_{\alpha,Bmk,i} \times (Bmk_{i,t}) + \theta_{\beta,Ret,i} \times (Ret_{i,t})] \times R_{m,t} + \varepsilon_{i,t}$$

Prior to the regression, each attribute is transformed into a zero mean and unit standard deviation z-score so as to avoid scale effects. The model is estimated over the S&P 500 universe with $N = 500$ stocks and the period 2002–15 (which corresponds to 51 quarterly returns). Hence we obtain 500 coefficients of each type (intercept, capitalisation sensitivity, book-to-market sensitivity and past return sensitivity) for the alpha, and 500 others for the beta. Figure 1 displays the distributions of the four coefficients that appear in the decomposition of the fundamental beta, and suggests that there is a substantial dispersion in the estimates across the 500 stocks.

Sector in multi-dimensional portfolio analysis with fundamental betas

Risk and performance analysis for equity portfolios is most often performed according to one single dimension, typically based on sector, country or factor decompositions. In reality, the risk and performance of a portfolio can be explained by a combination of several such dimensions, and the question arises to assess, for example, what the marginal contributions of various sectors are in addition to stock-specific

1. Distribution of coefficients in the more flexible one-factor model



The coefficients are estimated through time-series regressions for each of the 500 stocks from the S&P 500 universe with quarterly stock returns, z-score attributes and market returns from Ken French's library over the period 2002–15. Attributes come from the ERI Scientific Beta US database and are updated quarterly.

attributes to the performance and risk of a given equity portfolio. The fundamental beta approach can be used for this purpose, provided that one introduces a sector effect in the specification of the conditional alpha and beta. This is done by replacing the stock-specific constants $\theta_{\alpha,0,i}$ and $\theta_{\beta,0,i}$ by sector-specific terms, which only depend on the sector of stock i . The method can be easily extended to handle country effects in addition to sector effects. Formally, the model reads:

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t} \times R_{m,t} + \varepsilon_{i,t}$$

$$\alpha_{i,t} = \theta_{\alpha,0,s(i)} + \theta_{\alpha,Cap,i} \times Cap_{i,t} + \theta_{\alpha,Bmk,i} \times Bmk_{i,t} + \theta_{\alpha,Ret,i} \times Ret_{i,t}$$

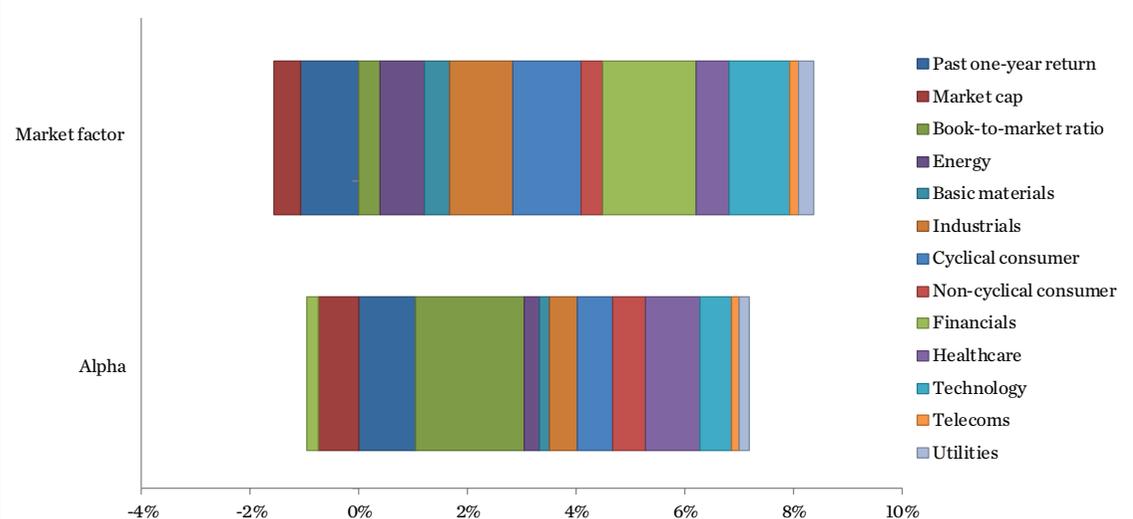
$$\beta_{i,t} = \theta_{\beta,0,s(i)} + \theta_{\beta,Cap,i} \times Cap_{i,t} + \theta_{\beta,Bmk,i} \times Bmk_{i,t} + \theta_{\beta,Ret,i} \times Ret_{i,t}$$

This model can be used to decompose the expected return and the variance of a portfolio conditional on the current weights and

constituents' characteristics. In figure 2, we show an application of this method to the analysis of the expected performance of a broad equally-weighted portfolio of US stocks. At the first level, expected return is broken into a systematic part – which comes from the market exposure – and an abnormal part. Each of these two components is further decomposed into contributions from sectors and continuous attributes.

As we can see, the book-to-market ratio has a positive impact both on market exposure and alpha, suggesting that a higher book-to-market ratio implies higher abnormal performance and market exposure, while the past one-year return has a positive impact on alpha but a negative impact on market exposure. Finally market capitalisation has a negative impact on both alpha and market exposure, confirming that large caps tend to have smaller abnormal performance and market exposure. Within market factor exposure and alpha contributions, some

2. Absolute performance decomposition of the EW S&P 500 index on market factor with fundamental alpha and fundamental beta



The coefficients of the one-factor model are estimated with a pooled regression of the 500 stocks from the S&P 500 universe. Data is quarterly and spans the period 2002–15, and market returns are from Ken French's library. Attributes (capitalisation, book-to-market and past one-year return) and sector classification come from the ERI Scientific Beta US database and are updated quarterly.

◀ sectors have larger contributions, such as financials, industrials and cyclical consumer for market exposure and healthcare for abnormal performance.

Targeting market neutrality with fundamental betas

We then compare the fundamental and rolling-window betas as estimators of the conditional beta by constructing market-neutral portfolios based on the two methods. We show that the fundamental method results in more accurate estimates of market exposures, since the portfolios constructed in this way achieve better ex-post market neutrality compared to those in which the beta was estimated by running rolling-window regressions, which tend to smooth variations over time thereby slowing down the diffusion of new information in the beta. In contrast, the fundamental beta is an explicit function of the most recent values of the stock's characteristics, and as such is more forward-looking in nature.

In order to achieve more robustness in the results, we do not conduct the comparison for a single universe, but we repeat it for 1,000 random universes of 30 stocks picked among the 218 that remained in the S&P 500 universe between 2002 and 2015. Hence we have 1,000 random baskets of 30 stocks, and, for each basket, we compute the two market-neutral portfolios.

Figure 3 shows that portfolios based on fundamental beta achieve, on average, better market neutrality (corresponding to a target beta equal to 1) than those based on time-varying historical beta, with an in-sample beta of 0.925 versus 0.869 on average across the 1,000 universes. We observe the same phenomenon in terms of correlation with an average market correlation of 0.914 for portfolios based on fundamental betas, versus 0.862 for the portfolios based on historical time-varying beta.

At each date, we also compute the 1,000 absolute differences between the five-year rolling-window beta and the target of 1, and the results are reported in figure 4. The historical method exhibits the largest deviation levels with respect to the target, with a number of dates (such as March 1996, December 2005 or March 2007) where the relative error exceeds 60%! In comparison, the fundamental method leads to much lower extreme differences between target and realised factor exposures, thus suggesting that this methodology allows for the error in the estimation of the conditional betas to be reduced versus what can be achieved with the classical rolling-window approach.

Fundamental betas and the cross-section of expected returns

The main goal of an asset pricing model is to explain the differences in expected returns across assets through the differences in their exposures to a set of pricing factors. It is well known that the standard CAPM largely misses this goal, given its inability to explain effects such as size, value and momentum. We investigate whether the fundamental CAPM is more successful from this perspective. To this end, we conduct formal asset pricing tests by using Fama and MacBeth method (1973). There are two statistics of interest in the output of these tests. The first one is the average alpha of the test portfolios, which measures the fraction of the expected return that is not explained by the model. The second set of indicators is the set of factor premia estimates, which should have plausible values.

More specifically, we test two versions of the conditional CAPM based on fundamental betas,

3. Targeting beta neutrality for maximum deconcentration portfolios based on fundamental and time-varying historical betas (2002–15)

	Out-of-sample market beta		Out-of-sample market correlation	
	Mean	Standard deviation	Mean	Standard deviation
Historical	0.869	0.032	0.862	0.025
Fundamental	0.925	0.035	0.914	0.020

1,000 maximum deconcentration portfolios of 30 random stocks subject to a beta neutrality constraint are constructed by using the rolling-window or the fundamental betas. The 30 stocks are picked among the 218 that remained in the S&P 500 universe for the period 2002–15, and the portfolios are rebalanced every quarter. The control regression on Ken French's market factor is done using quarterly returns over the period 2002–15. Market betas and correlations with the market return are computed for each portfolio over the period 2002–15 and are averaged across the 1,000 universes. Also reported are the standard deviations of the beta and the correlation over the 1,000 universes.

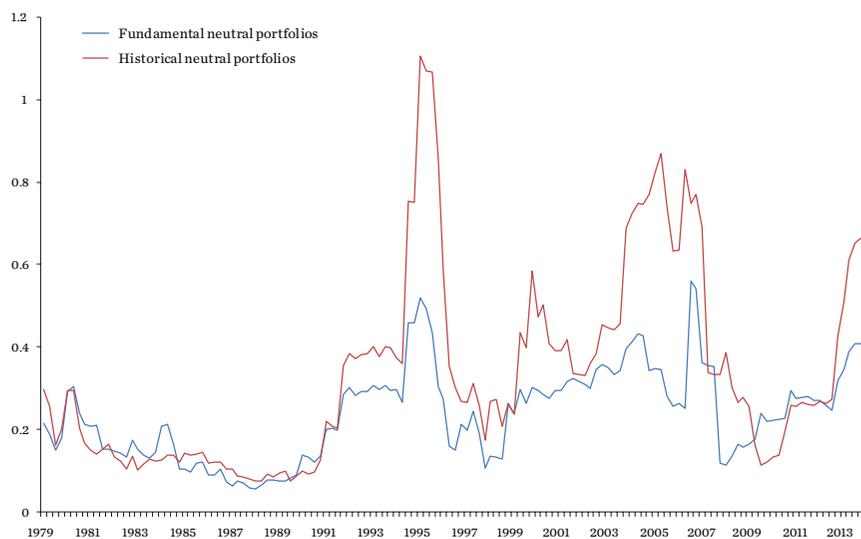
one with a constant market premium and one with a time-varying market premium. The latter approach is more realistic since it is well documented that some variables, including notably the dividend yield and the default spread, have predictive power over stock returns, at least over long horizons – see Fama and French (1988, 1989), Hodrick (1992) and Menzly, Santos and Veronesi (2004). Introducing a time-varying market premium implies that the unconditional expected return of a stock depends not only on its average conditional beta but also on the covariance between the conditional beta and the conditional market premium (Jagannathan and Wang [1996]).

In figure 5, we compare the distributions of alphas across the 30 portfolios for the four competing models. These results suggest that the parsimonious fundamental conditional CAPM

with constant market premium is substantially more effective than the standard static CAPM for explaining differences in expected returns, with an average alpha that is dramatically reduced from 5.04% down to 1.69%. Remarkably, this model performs as well as the less parsimonious Fama-French-Carhart four-factor model.

The results reported in the exhibit also suggest that accounting for the covariance term between the conditional beta and the conditional market premium further improves the ability of the fundamental CAPM to explain the returns of portfolios sorted on size, book-to-market or short-term past returns with respect to the case where the premium is constant. Furthermore, the average alpha obtained with this model is almost half the value obtained with Fama-French-Carhart model, suggesting that a conditional CAPM based on fundamental betas

4. Largest distance to 1 for the portfolio realised beta across 1,000 universes



1,000 maximum deconcentration portfolios of 30 random stocks subject to a beta-neutrality constraint are constructed by using the rolling-window or the fundamental betas. The 30 stocks are picked among the 71 that remained in the S&P 500 universe for the period 1970–2015, and the portfolios are rebalanced every quarter. The control regression on Ken French's market factor is done on a five-year rolling window of quarterly returns. For each window, the figure shows the largest distance to 1 computed over the 1,000 universes.

5. Alpha distribution over the cross-section of sorted portfolios

	Mean	Std	First quartile	Median	Third quartile	Mean corrected T-stats
Static CAPM	5.04%	2.74%	3.35%	4.95%	6.35%	1.66
Carhart model	2.87%	1.06%	2.35%	2.66%	3.57%	0.89
Fundamental CAPM	2.86%	2.72%	1.08%	2.76%	4.19%	0.79
Fundamental CAPM with time-varying market factor	1.69%	2.70%	-0.27%	1.54%	3.39%	0.71

This figure provides the distribution of the estimated alphas for 30 portfolios sorted on size, book-to-market or past one-year return. These alphas are obtained by performing Fama-MacBeth regressions for three pricing models. The fourth row shows the distribution of alphas obtained in the conditional CAPM with fundamental beta and a time-varying market premium. The fundamental beta is a function of the constituents' attributes. Regressions are done on the period 1973–2015. The last column shows the average t-statistics across alphas.

and a time-varying risk premium can capture the size, value and momentum effects better than the Fama-French-Carhart model, and this without the help of additional ad-hoc factors.

Parsimonious and forward-looking risk indicators for equity portfolios

Multi-factor models are standard tools for analysing the performance and the risk of equity portfolios. In the standard Fama-French-Carhart model, size, value and momentum factors are constructed by first sorting stocks on an attribute (market capitalisation, the book-to-market ratio or past short-term return), then by taking the excess return of the long leg over the short leg. While these models are substantially more successful than the standard CAPM at explaining cross-sectional differences in expected returns, the empirical link between certain characteristics and average returns can always be accounted for by introducing new ad-hoc factors in an asset pricing model. In the end, numerous patterns have been identified in stock returns, thus raising concerns about a potential inflation in the number of long/short factors and their overlap.

Our analysis suggests another meaningful approach for explaining the cross-section of expected returns, which consists in treating attributes of stocks as instrumental variables to estimate the exposure with respect to a parsimonious set of factors. As an illustration, we have focused on the conditional CAPM one-factor model, and we estimate a time-varying beta that is explicitly given by a linear function of the very same characteristics that define the three Fama-French-Carhart factors. We show that a conditional CAPM based on this fundamental beta can capture the size, value and momentum effects as well as the Fama-French-Carhart model, but without the help

of additional factors. The pricing errors are further reduced by introducing a time-varying market premium, which introduces the cyclical covariation between fundamental betas and the market risk premium as a driver of expected returns. The fundamental beta also provides an alternative measure for the true unknown value of the conditional beta. This estimate is a function of observable variables and is not subject to the artificial smoothing effect that impacts betas estimated by a rolling-window regression analysis. Since the fundamental beta immediately responds to changes in the value of a stock's attributes, they can be used to more effectively assess the impact of a change in the portfolio composition on the factor exposure. We illustrate these benefits by constructing market-neutral portfolios based on the fundamental and rolling-window methods, and we show that the former approach achieves better out-of-sample neutrality. Interestingly, this approach can be extended in a straightforward manner from a single-factor model to a multi-factor model, thus allowing exposure to a variety of underlying systematic macro factors to depend upon the micro characteristics of the firm.

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New frontiers in smart beta investing: benefits and limits of traditional and alternative bond benchmarks

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Existing bond benchmarks as ill-diversified bundles of unstable factor exposures

Over recent years, a number of concerns have been expressed about the (ir)relevance of existing forms of corporate and sovereign bond indices offered by index providers (Reilly and Wright [2006]).¹

One of the major problems with bond indices which simply weight the debt issues by their market value is the so-called “bums’ problem” (Siegel [2003]). Given the large share of the total debt market accounted for by issuers with large amounts of outstanding debt, market-value-weighted corporate bond indices will have a tendency to overweight bonds with large

- ➔ A number of index providers have launched new forms of alternative indices to try to address some of the challenges with traditional weighting schemes based on the market value of debt.
- ➔ A number of ad-hoc alternative weighting schemes have been proposed but these initiatives have no academic grounding, and it is unclear whether the portfolios thus constructed would be optimal benchmarks under any reasonable assumptions.
- ➔ We provide a broad overview of these initiatives, which can be broadly classified into two different categories – fundamental approaches and diversification approaches.
- ➔ Our main conclusion is that none of these approaches successfully addresses all the key concerns and challenges involved in designing a truly investor-friendly bond benchmark, which suggests that further work is needed in the area of bond benchmarks.

amounts of outstanding debt. It is often argued that such indices will thus give too much weight to riskier assets. While it is debatable whether debt-weighting really leads to the most risky securities being over-weighted², it is clear that market-value debt-weighted indices lead to concentrated portfolios that are in opposition with investors’ needs for efficient risk premia ▶

² A higher weight for an issuer with a high market value of debt does not necessarily mean that the index is overweighting issuers with a high face value of debt. An issuer with a high amount of par value debt outstanding will only get a high weight if the market value is relatively close to par value which implies that the issuer is not perceived to be very risky. It is therefore not clear why the market-value-weighted index should become riskier. In addition, loading onto riskier issuers should not be a problem if this risk is rewarded by higher expected returns.

¹ See also Reilly, Kao and Wright (1992) for an early analysis of bond indices.

◀ harvesting, which involves holding well-diversified portfolios. In a nutshell, a good case can be made that existing bond indices tend to be poorly diversified portfolios, regardless of whether or not the over-weighting applies to the wrong constituents. A similar problem has been documented for equity indices – see for example Amenc, Goltz and Le Sourd (2006).

In addition to the problem of concentration, fluctuations in risks' exposure (such as duration or credit risk in existing indices) are another source of concern – see Campani and Goltz (2011) for more detail. Such uncontrolled time variation in risk exposures is incompatible with the requirements of investors that these risk exposures be relatively stable so that allocation decisions are not compromised by implicit choices made by an unstable index. For example, an asset-liability mismatch would be generated by changes in the duration of the bond index if the latter is used as a benchmark for a pension fund bond portfolio.

More generally, it appears that existing bond indices can be regarded as more 'issuer-friendly' than 'investor-friendly', in the sense that these bond indices passively reflect the collective decisions of issuers regarding the maturity and size of bond issues, with no control over risk factor exposures associated with such choices nor over the reward that investors should deserve from holding a well-diversified portfolio of such factor exposures.

Alternative bond benchmarks as partial and ad-hoc answers to otherwise well-identified questions

Recently, a number of index providers have launched new forms of alternative indices to try to address some of the challenges with traditional weighting schemes based on the market value of debt. A number of ad-hoc alternative weighting schemes have been proposed but these initiatives have no academic grounding, and it is unclear whether the portfolios thus constructed would be optimal benchmarks under any reasonable assumptions.

In what follows, we provide a broad overview of these initiatives, which can be broadly classified in two different categories – fundamental approaches (Arnott et al [2010]) and diversification approaches (Deguest et al [2013]).³ Our main conclusion is that none of these approaches successfully address all key concerns and challenges involved in designing a truly investor-friendly bond benchmark, which suggests that further work is needed in the area of bond benchmarks.

Fundamental approaches to bond indices address neither concentration risks nor factor exposure risks

Fundamental indexing in the bond market is a direct transfer of methodologies originally developed for equities. Promoters of fundamentally-weighted corporate bond indices include Research Affiliates, with a partnership format, and Barclays, with the so-called Issuer Corporate Bond index launched in September 2010. Research Affiliates has also developed a fundamentally-weighted sovereign bond index in partnership with Ryan Lab, and fundamentally-weighted sovereign bond indices have also

been launched by Lombard Odier Investment Managers (the LOIM Sovereign Bond index, launched in December 2010) and BlackRock (the BlackRock Sovereign Risk index, launched in June 2012).

The methodology used by Research Affiliates is explained in Arnott et al (2010). For corporate bond indices, the authors use the following five factors to assign a score to each corporate bond (investment grade and high yield): book value of assets, total dividends, total cash-flow, sales and face value of the debt issue. First, weights are computed for each corporation, and with respect to each factor, by using the trailing five-year average of each of the above metrics over the aggregate five-year average across all corporations. While it might seem unclear why it would be desirable to use a five-year trailing value as opposed to the current value for the fundamentals, the main practical motivation for this ad-hoc procedure is that the implied smoothing will lead to a reduction in turnover. Then, the composite measure is obtained by equally weighting four of the measures: assets, dividends, cash flow and sales. For emerging market sovereign bonds, the approach developed in Arnott et al (2010) is based on the following factors: total population, square root of land area (as a crude approximation for resources), total gross domestic product, energy consumption and face value of the debt issue. Similarly to the case of corporate bonds, weights are first computed for each country, and with respect to each factor, by using smoothed five-year averages of the above metrics over the aggregate metric across all countries. Then, a country's aggregate weight is the equally weighted average of its score on the individual factors.

The fundamental approach for constructing a bond index raises several concerns. First of all, the methodology used does not address the concern over stability of factor exposure. Moreover, the problem of concentration is approached with a purely ad-hoc methodology, and better diversified portfolios could be constructed on the basis of standard risk models being used. More importantly, it is unclear why some backward-looking trailing average of some arbitrarily selected variables (eg, square root of land area) should contain more useful information than say bond ratings, which for all their flaws are based on a much richer information set.

In the same spirit, a number of institutions (investment banks, index providers or asset managers), including Barclays Capital, Euro MTS and PIMCO, have launched sovereign bond indices using exclusively GDP measures to adjust the weights allocated to various regions, with methodological details varying across different providers. All these indices based on the GDP metric (and sometimes adjusted with other macroeconomic factors) give a relatively lower weight to countries that are heavily indebted. Therefore, using GDP-based indices deals with only one drawback of cap-weighted indices, which is the concentration. Additionally, relying exclusively on GDP statistics may introduce a significant backward-looking bias since such data are updated on a quarterly basis. Moreover, the sensitivity to interest rate risk is not controlled, and the diversification of the issuers is not properly taken into consideration through suitable risk models, which may lead to such portfolios being heavily loaded on the same risk.

Ad-hoc diversification approaches to bond indices address concentration risk, albeit in an ad-hoc manner, but do not address factor exposure risks

The first ad-hoc approach to cope with the

problem of concentration risk involves imposing maximum limits to weights assigned to any particular constituent or issuer. BarCap for instance is trying to limit such concentration by capping issuer weights to a fixed percentage of the index and then redistributing the excess weight across the other issuers (for instance the Barclays Capital US Corporate Aaa–A Capped index is market-cap weighted with a 3% cap).

Extending the concept, equally-weighted indices, offered for example by Dow Jones, assign the same weight to each bond. The index contains only 96 bonds, which makes it easier to replicate than popular cap-weighted indices such as those of Barclays or Bank of America Merrill Lynch, and therefore avoids illiquidity issues. Investment grade bonds that qualify for inclusion (issued in the US, and with an outstanding value of at least \$500m) are classified into one of the three sectors: financials (48 bonds), industrials (36 bonds) or utilities (12 bonds), and into one of four maturity cells. On the one hand, this index offers the advantage of dealing with the bums/concentration problem, since the amount of debt issued does not impact the weighting scheme (even though the number of issues may have an impact). On the other hand, it does not address the lack of duration control, and may exhibit higher turnover levels than cap-weighted indices since maintaining the precise sector and maturity repartitions of the index induce more frequent rebalancing than in the case of buy-and-hold market-cap weighted indices, which require trading only when the index constituency changes over time.

As opposed to imposing an identical dollar contribution from various constituents of the bond index universe, one may seek to impose an identical risk contribution from all constituents – such is the focus of inverse duration weighted bond indices for which the weight assigned to each bond is equal to the inverse of the (modified) duration of the bond taken as a proxy for the risk level of the bond. Duration weighting implies that the overall duration of the index is equal to the number of constituents; this index achieves both stability of factor exposure as well as some form of portfolio diversification. Nothing guarantees, however, that this ad-hoc portfolio construction methodology should lead to a benchmark with attractive risk-adjusted characteristics.

Risk-based diversification approaches to bond indices may satisfactorily address concentration risk but also do not address factor exposure risks

Given that ad-hoc methodologies are not likely to offer satisfactory solutions to investors' needs, the question arises as to whether one could use risk models to construct improved bond benchmarks with a focus on enhancing diversification, controlling risk exposure, and subject to implementable levels of turnover and liquidity constraints.

The abundance of theoretical and empirical research on the performance of portfolio optimisation techniques in the equity universe stands in sharp contrast to the relative scarcity of research about how to form bond portfolios with attractive risk/reward performance from an out-of-sample basis. For example, there is no readily available answer in the academic literature to fundamental questions such as whether an investor in sovereign or corporate bonds would be better off investing in an equally-weighted combination of available bonds versus an optimally chosen combination on the basis of careful parameter estimates. The notion that

³ We do not discuss here the liability-driven approaches such as the Markit iBoxx US Pension Liability indices, the Barclays US Treasury Targeted Exposure index series, or the Ryan Strips index family, which have a different objective, namely hedging/replicating risk factor exposures in investors' liabilities, as opposed to efficient (also known as smart) harvesting of risk premia.

bonds are often held as part of investors' hedging portfolios is not a sufficient reason for ignoring the need to generate attractive risk-adjusted performance. After all, as indicated above, there are an infinite number of bond portfolios with a given target duration, and selecting the one with the highest risk/reward ratio should intuitively improve investor welfare. Besides, Treasury and corporate bonds are also natural ingredients within investors' performance-seeking portfolios, where the focus lies precisely on maximising the risk/reward ratio.

In a series of research papers – Deguest et al (2013) and Deguest et al (2014) – we have attempted to extend the existing literature, which has mostly focused on the equity universe, by providing the first formal out-of-sample comparative analysis of the performance of various bond portfolio optimisation models in the presence of duration constraints. At each rebalancing date, we first impose a no-arbitrage restriction that allows us to decompose all bonds available in a given universe into a sum of fictitious pure discount bonds matching coupon or principal payment dates and amounts. In a second step, we use the transition matrix from pure discount bond prices to coupon-paying bond prices obtained in step one to extract a consistent covariance matrix for non-stationary coupon-paying bond returns from the covariance matrix for stationary constant maturity pure discount bond returns. This procedure ensures the respect of no-arbitrage conditions, as well as the respect of the structure inherent to bond prices (eg, the convergence of bond return volatility to zero when approaching maturity). In a third step, we robustify the covariance matrix for coupon-paying bonds obtained in step two using a factor model for the term structure. In the empirical analysis, the factors are extracted from a principal component analysis of the return on coupon-paying bonds, with the first two factors (interpreted as

the level and slope of the yield curves) typically explaining an exceedingly large fraction of the bond return variance.

More work is needed for efficient harvesting of risk premia in the fixed-income universe

Using risk parameter estimates obtained as described above, as well as expected return estimates based on the parsimonious prior of a constant reward for the few selected risk factors, we have found that the use of Sharpe ratio maximisation techniques generates an improvement in investors' welfare compared to the use of ad-hoc bond benchmarks such as equally-weighted (EW) or cap-weighted (CW) portfolios. In addition to maximum Sharpe ratio (MSR) maximisation, we also test different heuristic portfolio optimisation models, including minimum concentration (MC) portfolios (which correspond to the closest approximation of an equally-weighted strategy subject to constraints such as duration or weight constraints), global minimum variance (GMV) portfolios and diversified risk parity (DRP) portfolios, also known as factor risk parity portfolios – see Deguest, Martellini and Meucci (2013).

While the encouraging results we have obtained for both sovereign and corporate bonds suggest that improved bond benchmarks can be constructed with improved characteristics in terms of concentration risks, the lack of liquidity of some bond issues implies that great care should be applied in ex-ante filtering of the investment universe.

Most importantly perhaps, the modern approach to factor investing – Amenc, Goltz and Martellini (2013) – suggests that we should first identify robust and economically motivated sources of risk in fixed-income markets before applying a weighting scheme. In this context, it appears that more work is required both in academia and in the industry to start

addressing such challenges in a careful way, before we are able to see the emergence of improved bond benchmarks that will provide adequate answers to investors' needs. The contribution by Riccardo Rebonato entitled 'Smart beta strategies in fixed income' in this supplement (see below) will provide a wealth of useful insights with respect to the benefits and challenges associated with risk premia harvesting in fixed-income markets.

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Smart beta strategies in fixed income

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In the last decade, the search for priced non-market equity risk factors, and the implementation of smart beta strategies for equities have been a major focus of applied and theoretical research. It is now generally acknowledged that, in the equity space, these strategies permit the construction of more desirable portfolios than naive passive allocations (such as equal or market-capitalisation weighting schemes).

Recently, this focus has been shifted to other asset classes (see, eg, Asness, Moskowitz and Pedersen [2013]) and to fixed income in particular. Given the huge size of the fixed-income market¹, the natural question is whether smart beta strategies will prove effective for this asset class.

In this article:

- we put the search for factors and beta strategies in the context of asset pricing, and we show that compensation for non-market factors is not just allowed, but actually required, by financial theory;
- we explain the different, and complementary, questions answered by time-series and cross-

- The question arises as to whether smart beta strategies will prove effective for the fixed-income asset class.
- We put the search for factors and beta strategies in the context of asset pricing, and we show that compensation for non-market factors is not just allowed, but actually required, by financial theory.
- We explain the various questions answered by time-series and cross-sectional analyses of risk premia and then focus on fixed-income instruments, presenting the time-series and cross-sectional formulations for the search of priced risk factors.
- We finally explain the unique challenges encountered in identifying priced risk factors in fixed-income products and present the main findings obtained to date.

sectional analyses of risk premia;

- we then focus on fixed-income instruments, and present the time-series and cross-sectional formulations for the search of priced risk factors;
- we explain the unique challenges encountered in identifying priced risk factors in fixed-income products;
- we present the main findings obtained to date;
- we suggest avenues for fresh research.

Throughout the presentation, we emphasise the dangers of data mining, and therefore place great emphasis on the importance of finding some cogent explanation for the putative factors.

Excess returns – background

In the first incarnation of the 'modern' approach to asset pricing – the body of work that, starting from Markowitz (1952), led to the CAPM (Treyner [1961], Sharpe [1964], Lintner [1965]) – the excess return earned by any security was derived to be proportional (via the famous 'market beta') to a single factor – the market excess return over the riskless rate. ▶

¹ According to the BIS, the size of the global debt market is approximately \$22trn (as reported in the *Financial Times*, 10 November 2016, page 18, Lex).

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*Average of the differences in Sharpe ratio and differences in annualised excess returns observed between December 31, 1975 and December 31, 2015 (40 years) for all long-term track record Scientific Beta High-Factor-Exposure Diversified Multi-Strategy indices (SciBeta High-Factor-Exposure Value Diversified Multi-Strategy, SciBeta High-Factor-Exposure Low-Volatility Diversified Multi-Strategy, SciBeta High-Factor-Exposure Mid-Cap Diversified Multi-Strategy, SciBeta High-Factor-Exposure High-Momentum Diversified Multi-Strategy, SciBeta High-Factor-Exposure High-Profitability Diversified Multi-Strategy and SciBeta High-Factor-Exposure Low-Investment Diversified Multi-Strategy) and their Scientific Beta cap-weighted factor equivalents calculated on a universe of the 500 largest-capitalisation US stocks.

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

◀ As a corollary to this result, it followed that (barring leverage) increasing exposure to the market factor was the only way for an investor to increase excess return.

The CAPM has fared better theoretically, and indeed among practitioners,² than empirically. Indeed, statistical tests have robustly and convincingly rejected the validity of the CAPM model. This rejection did not imply, however, that the market factor played no role in explaining excess returns. Rather, the empirical studies revealed the untenable claim that the market factor was the only factor, and suggested that additional, non-market, factors, could have significant explanatory power: the market risk factor had to be complemented by other explanatory variables, these empirical studies said, not tout court jettisoned. These empirical studies were silent, however, as to the nature of the additional factors.

Is it reasonable to accept the existence of non-market factors? It certainly is, both normatively and descriptively. A positive risk premium reflects the compensation for the fact that a security is expected to pay well in states of the world when investors are doing well (high-consumption states), and to have poor payouts when investors feel poor (low-consumption states). Now, the CAPM implicitly assumes, among other things, that investors only draw their income (and hence derive their consumption) from their investment portfolios. If this were true, high and low consumption would indeed only be linked to the performance of the market portfolio.

In reality, investors face a number of macroeconomic risks to their consumption stream: unemployment, for instance, would affect their labour income; inflation would erode the nominal value of their nominal assets; productivity shocks are known to be related to stock returns³ etc.

In principle, every source of consumption risk can therefore command a compensation for bearing that risk, and hence a risk premium.

This line of thought led to extensions of the CAPM model in which several consumption-affecting factors were allowed to influence the expected returns of stocks.⁴ This, in turn, motivated, or at least provided the theoretical justification for, the empirical search of non-market factors.

In parallel, studies in behavioural finance and in the institutional workings of financial markets pointed, on the one hand to the bounded rationality of investors,⁵ and on the other to the ‘frictions’ that taxes, laws, and regulations impose on the functioning of the financial system. For the present discussion the important point is that both these sources of ‘imperfection’ (‘irrationalities’ and ‘frictions’) could in

principle introduce new explanatory variables (which may, but need not, be proper ‘factors’) to account for excess returns.

An expression for the factors

These qualitative considerations can be made more precise as follows.

Consider first the statistical regression of the excess return, r_i , over the riskless rate, r_f , from security i , on the market excess return, $r_m - r_f$:

$$r_i - r_f = \alpha_i + \beta_i^m (r_m - r_f) + \varepsilon_i \quad (1)$$

If we take equation (1) purely as a statistical regression, there are no constraints on the intercepts. As we discussed, the CAPM makes the strong statement that all the intercepts, α_i , should be statistically indistinguishable from zero, (and that the residual should be uncorrelated with the left-hand variables).

If one empirically finds, as one does, that some intercepts are statistically different from zero, then finding ‘factors’ can be described as the identification of n non-market-return variables, x_i , such that

$$r_i - r_f = \alpha_i' + \beta_i^m (r_m - r_f) - \sum_{k=1, n} \beta_i^k x_k + \eta_i \quad (2)$$

with the new intercepts of α_i' now either zero or at least such that

$$\sum w_i |\alpha_i'| < \sum w_i |\alpha_i| \quad (3)$$

(In the equation above, the quantities w_i are the weights in the market portfolio.) The identification of new factors turns at least a part of the ‘undigested’ intercepts of the CAPM-inspired regression (the α_i in equation (1)) into new interpretable ‘betas’ (the β_i^k in equation (2)).

In the equity space, where most of the theoretical and empirical work has been carried out, Fama and French (1993) pioneered the search for the factors x_k . In their early work they identified, in addition to the market portfolio, two additional factors: the small-minus-big factors, and high-minus-low factor (where ‘small’ and ‘big’ refer to the size of a firm, and ‘high’ and ‘low’ to the ratio of the book to market value).⁶

In the wake of these findings, an immense literature blossomed on the search for additional explanatory variables of excess returns. Regression studies which directly used macroeconomic variables as factors were met with limited success. Given the difficulty to quantify macroeconomic variables (think, for instance, of creating a time series of productivity shocks), the practices therefore became common first to use well-identifiable traded proxies,⁷ and then to use an array of market-observable variables that were posited to have some link to a consumption risk story.

The degree of theoretical rigour and statistical robustness of these studies varied greatly.⁸ So, alongside the factors that traditional asset pricing theory would readily understand, a richly populated menagerie of more opaque ‘anomalies’ was born.⁹ Admittedly, it did not always prove easy – albeit not beyond the ken of an ingenious financial economist – to ‘map’ these empirically determined factors to the sources of consumption risk that would justify calling them ‘factors’.

After the initial research dust settled, the academic and practitioner consensus in equities finally coalesced around the proposition that a small number of robust factors (from which the small-minus-big was often dropped and to which the momentum frequently added) could be identified.

When a statistically sound and economically principled approach to factor identification has been employed, the implications of these findings for asset management have been profound. As new, robust (and sometimes economically interpretable) factors were identified, portfolio weighting schemes other than the market capitalisation were soon created in the equities arena that would tilt the portfolio composition towards the non-market rewarded factors.

The degree and nature of the weight tilt would be determined in such a way as to exploit diversification in order to obtain what the CAPM had claimed to be unattainable: a higher-than-CAPM return for the same risk; or a lower-than-CAPM risk for the same return. Since in the old CAPM world the only way to gain extra unleveraged return was to increase the exposure to the market beta, the new, CAPM-beating portfolio weighting schemes became known as ‘smart beta’ strategies. Their success in the equity space has been widely documented, and it is now an established, text-book ‘fact’ of asset pricing. See, eg, Ang (2014).

Smart beta: from time-series to cross-sectional analysis for fixed income

Until very recently, the search for risk premia and excess returns had a very different complexion in the fixed-income arena. Most of the studies were focussed on (mainly US-issued) Treasury bonds, for which good quality data has been available for decades. However, the high degree of correlation amongst Treasuries (it is well known that two or three principal components explain over 95% over the observed price variations) makes the identification of cross-sectional differences less promising than for equities. Time series analysis of excess returns has therefore been prevalent for government bonds, and the associated research programme that until very recently was their staple diet of risk-premium research in fixed income can be summarised as follows.

Given a set of state variables, x_t , that describe the (typically Treasury) yield curve (such as principal components), under no-arbitrage the time- t returns on a fixed-income bond of maturity T , P_t^T , are given by

$$\frac{E[P_{t+dt}^T] - P_t^T}{P_t^T} = \left(r_t^f + \frac{1}{P_t^T} \sum_i \frac{\partial P_t^T}{\partial x_i} \lambda_i \sigma_{x_i} \right) dt \quad (4)$$

where σ_{x_i} is volatility of the i -th factor and λ_i its associated market price of risk.

If the ‘market prices of risk’ are assumed to depend on the state variables,

$$\lambda_i = \lambda_i(x_1, x_2, \dots, x_n)$$

the search for time- (state-) dependent risk premia boils down to ▶

2 “Even though the CAPM is firmly rejected by data, it remains the workhorse of finance: 75% of finance professors advocate using it, and 75% of CFOs employ it in actual capital budgeting decisions”, Ang (2016), page 197, emphasis added. See also Welch (2008) and Graham and Harvey (2001), quoted therein.

3 Ang (2016) reports a 48% correlation between a five-year moving average of productivity shocks and stock returns. In real business cycle models, productivity shocks affect not only stock returns, but also growth, investments and savings, and therefore indirectly affect non-investment consumption – for instance, through wage growth.

4 The first to include macro factors in equities in the cross-sectional search for systematic source of risk were Chen, Roll and Ross (1986).

5 And to the difficulty to arbitrage these irrationalities away (see, eg, Shleifer and Vishny [1997]).

6 More precisely, the Fama and French factors were factor-mimicking portfolios, ie, long-short portfolios of stocks that would mimic the factors of interest.

7 For instance, the VIX index is an obvious proxy for volatility risk.

8 As Fama famously said, abandoning the requirement to link a factor to a cogent consumption story was equivalent to issuing a “fishing licence”. The dangers of data mining are particularly salient in this context, given the large amount of data required to create a training and a back-testing set. See, eg, Abu-Mostafa, Magdon-Ismail and Lin (2012) in this respect.

9 The distinction between ‘true’ risk factors and ‘anomalies’ is not a purely nominal one: ‘true’ risk factors are not washed away by discovering them, as they remain the market compensation for receiving large payoffs in good states of consumption, and vice versa. Behaviourally driven irrationalities, instead, may be corrected by sufficiently well capitalised arbitrageurs (such as hedge funds); and as for institutional frictions, these can disappear at the stroke of a regulatory pen.

➔ identifying for which state variables the market price of risk is not zero;
 ➔ for these ‘rewarded’ state variables, identifying the dependence of the market price of risk on the state variables – in the last decade there has been the vibrant research programme associated with the search for the return-predicting factors, ie, with linear combinations of state variables which have ex ante (predictive) power about the sign and magnitude of the excess returns.

For instance, for Treasuries, the rewarded variable has been found to be the (uncertainty in) level of the yield curve (the first principal component), but the magnitude of the reward mainly depends on the return-predicting factor slope (the second principal component). Of course, the dependence of the market price of risk on the state variables introduces time dependence to the risk premia.

Until the mid-2000s cutting-edge research in Treasury risk premia was (and still is) focused on the identification of return-predicting factors more efficient than the slope. See, eg, Cochrane and Piazzesi (2005), Cieslak and Povala (2010a, 2010b), and the references therein.

Time series and cross-sectional studies are both valuable, but answer different questions. When the state and time dependence of the risk premium for a given asset class is investigated via a time-series analysis and the identification of a return-predicting factor, the question being answered is whether ‘today’ is a good or bad time to invest (be ‘overweight’) in the asset class as a whole. When the cross-sectional differences within a given asset class are explored, the question being answered is to which securities within the asset class one should give more weight, given that an investment in that asset class ‘has to’ be made.

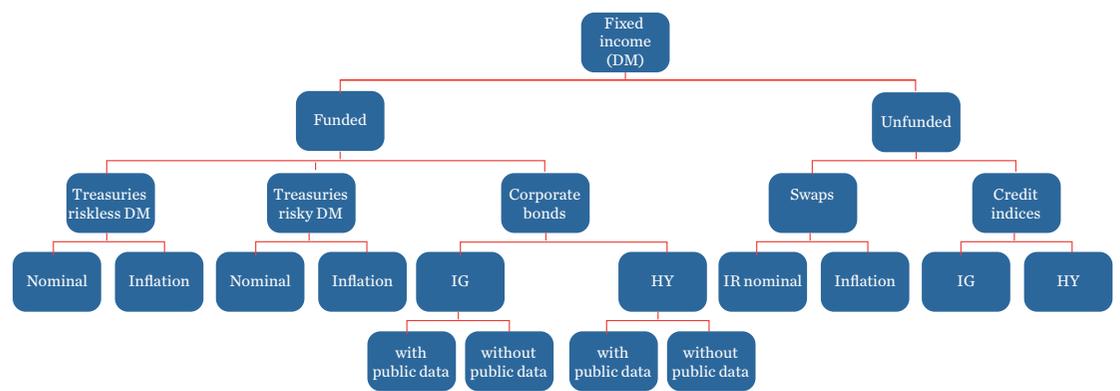
In the fixed-income area, time-series analysis has typically resulted in the decision of whether to construct a portfolio with longer or shorter duration than the benchmark. A cross-sectional analysis has typically been approached via cheap/dear analysis using empirical (Nelson-Siegel [1987]) or structural (see, eg, Kim-Wright [2005], or Adrian, Crump and Moench [2014, 2015]) models. In the fixed-income area, this type of analysis has usually been ‘tactical’ in nature, and has typically given rise to the construction of duration-neutral relative-value portfolios.

This state of affairs is rapidly changing. In the past few years practitioners and academics have begun to look at fixed-income products from a smart-beta (cross-sectional) perspective. Given the size of the international government and corporate debt outstanding, the lateness of this development is at first blush surprising. This lateness can be partly accounted for by the relative poverty of the data quality for large sections of the fixed-income universe. Another, and arguably more compelling, explanation is the sheer complexity of the fixed-income lay of the land, some salient aspects of which are shown in figure 1 (which only looks at developed markets).

As the figure shows, under the capacious tent of the ‘fixed-income’ denomination one gathers

- ➔ truly riskless government debt;
- ➔ ‘somewhat’-to-extremely credit-risky government debt;
- ➔ corporate debt that ranges in creditworthiness from better than most government instruments to junk;
- ➔ real and nominal bonds (which come in government and corporate flavour);
- ➔ funded and unfunded (ie, cash versus swap) instruments;
- ➔ corporates for which public data are available

1. The fixed income landscape for developed markets (DM)



(and for which accountancy-related characteristics can be extracted) and corporate for which this is not possible.

Securitised products have been excluded from this classification.

Not surprisingly, empirical studies so far have focused on (often rather limited) subsections of this investment universe. We briefly review in the next section some of the more salient findings.

Empirical findings to date

Looking at the results with a broad brush, one can say the following.

For corporate bonds, it is easy to explain yield changes, but difficult to explain spread changes. When the attempt has been made to find explanatory variables to account for spread changes (see, eg, Collins-Dufresne, Goldstein and Martin [2001]), both the theoretically-motivated variables¹⁰ and the ad-hoc factors have been shown to have a limited explanatory power, with R^2 ranging from 19% to 25%.

It was also found that the first principal component of the residuals could explain a very large proportion of the observed variability. Therefore firm-specific factors are unlikely to account for the residuals: there is likely to be an important systematic factor that can account for the bulk of changes in credit spreads (as opposed to in yields), but we still don’t really know what it is.

One could, of course, take the first principal component of the residuals as the ‘factor’, but this would not allow any meaningful economic interpretation, and there would be no guarantee of the stability of this factor.

Howling and van Zundert (2014) find empirical evidence that “the size, low-risk and momentum factors have economically meaningful and statistically significant risk-adjusted returns in the corporate bond market”. They find that their factors can be combined to form a more attractive (better Sharpe ratio) overall portfolio, and that the results are robust when transaction costs are included, when the factor proxies are defined somewhat differently, and when the portfolios are built in different but reasonable ways.

The low-risk factor is echoed in the work by de Carvalho et al (2014), who find that low-volatility bonds have better Sharpe ratios than high-volatility bonds. However, the Sharpe ratio

associated with some of these low-volatility portfolios may well be high, but the leverage required to make the expected returns comparable to, say, expected returns from equities can be as high as 50 or 60. (This, by the way, may well be an explanation of why the ‘anomaly’ is there in the first place.)

It has been claimed that more efficient portfolios can be built by reducing exposure to corporates or sectors with large issuance size. For individual corporates, of course, the variable of interest is leverage, not debt size per se, but this quantity is only computable for companies with public data. As for ‘excessive’ issuance in particular sectors, the ‘explanation’ of why size may be negatively correlated with performance points to debt issuance ‘bubbles’ (such as the volume of issuances for telecoms or tech companies in 2000, or for financials in 2005–06).

Liquidity affects different issuers to very different extents, and is poorly correlated with creditworthiness: Italy, for instance, has a similar credit spread (to Bunds) as Spain, but the issuance size, and hence the normal-times liquidity, is much larger in BTPs than in Bonos. Much work needs to be done in this area, which is one of the least explored (probably because of the difficulty in constructing ‘non-tautological’ proxies).

Momentum has been observed in fixed income as well, but the choice of the trailing window is delicate and the optimal choice for the length of the momentum ‘run’ is not universal. Short-term mean reversals have been observed to compete with momentum, complicating the analysis.

Value has been found difficult to define in the case of bonds. For issuers for which reliable yield curves can be built (mainly government bonds, bonds issued by semi-government agencies, and a handful of corporates) cheap/dear analysis has been successfully undertaken by market practitioners for a long time, but few, if any, systematic studies have appeared in the literature. Asness, Moskowitz and Pedersen (2013) provide a (not obviously intuitive) proxy for value, and find that high ‘value’ bonds tend to perform better than low ‘value’ ones.

It must be stressed that evidence of value and momentum factors has been found across a number of asset classes (stocks, Treasuries, corporate bonds, currencies, commodities). This suggests that ad hoc explanations are unlikely to be valid: “The strong correlation structure among value and momentum strategies across such diverse asset classes is difficult to reconcile under existing behavioural theories, while the high Sharpe ratios of a global [...] diversified

¹⁰ If one looks at a risky debt from an option-theoretical perspective (a put on the value of the assets), one would expect volatility, the interest rate level and the degree of in-the-moneyness to affect the value of the default option. These were the ‘fundamental’ quantities.

portfolio presents an even more daunting hurdle for rational-risk-based models” (Asness, Moskowitz and Pedersen [2013]).

Finally, the ‘fallen angels’ effect (which is a classic example of a ‘friction’ generated by a regulatory-like constraint) seems to still be present, although downgrade-tolerant strategies are becoming increasingly widespread.

Conclusions

In this note, we have put in context the recent cross-sectional studies of excess returns in the fixed-income space. We have highlighted both the promises and the difficulties associated with the identification of these fixed-income factors. Many seem to be variants of the factors that have already been identified for equities. As the value factor shows, however, the ‘transliteration’ from one asset class to another often requires careful handling.

A convincing economic interpretation of the factors remains elusive: if anything, having found similar factors at play in the fixed-income market makes their economic justification more, not less, challenging.

Overall, it seems fair to say that ‘fixed-income smart beta’ is an exciting new area of research, where a lot of empirical and theoretical work still needs to be carried out to build a convincing, and practically exploitable, understanding of which factors are ‘really there’, of why they exist in the first place, of how they can be best captured, and of how desirable portfolios can be built.

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Initial margin for non-centrally cleared OTC derivatives: overview, modelling and calibration

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In a recent report¹ produced as part of the French Banking Federation (FBF) chair on banking regulation and innovation under the aegis of the Louis Bachelier laboratory in collaboration with the Fondation Institut Europlace de Finance (IEF) and EDHEC, we provide a detailed overview and analysis of the framework used by large financial institutions to determine initial margin (IM) and variation margin (VM) payments when trading non-cleared over-the-counter (OTC) derivatives. This new framework, which came into effect in September 2016, is based on the recommendations of the BCBS/IOSCO Working Group on Margin Requirements (WGMR)² which were set out in BIS (2015).

This framework has been in development since it was first proposed following the Pittsburgh G20 meeting in 2009. It was a response to the events of September 2008 which saw the bankruptcy of Lehman Brothers, the bailout of AIG and the federal takeover of Fannie Mae and Freddie Mac, all of which had large exposures to the OTC derivatives market. In the US, the framework has been implemented by the Com-

- We provide an overview and analysis of the framework used by large financial institutions to determine initial margin and variation margin payments when trading non-cleared over-the-counter derivatives.
- This new framework, which came into effect in September 2016, is based on the recommendations of the BCBS/IOSCO Working Group on Margin Requirements.
- The new margining regulations for the non-cleared OTC derivatives are the main subject of our study. Their purpose is to reduce systemic risk across financial markets.
- We summarise our observations on the new regulation in 18 points.

1 O’Kane, D. (June 2016). Initial Margin for Non-Centrally Cleared OTC Derivatives – Overview, Modelling and Calibration. EDHEC Risk Position Paper.

2 The BCBS is the Basel Committee on Banking Supervision and IOSCO is the International Organization of Securities Commissions. The group responsible for the framework is the Working Group on Margin Requirements (WGMR).

3 See ISDA (2014b).

modities Futures Trading Commission (CFTC) within the framework of the Dodd-Frank Act Title VII. In Europe the rules will be implemented within the new EMIR directive of the EU.

Since Pittsburgh, new regulations have accelerated the separation of the OTC derivatives market into a cleared and non-cleared market, with the former focusing on the ‘standard’ OTC derivatives. As of the end of 2013, the size of the non-cleared segment of the interest rate derivatives market alone was approximately \$123trn–141trn.³ The new margining regulations for the non-cleared OTC derivatives are the main subject of our study. Their purpose is to reduce systemic risk across financial markets. In this report we have provided an overview of these new regulations and summarise our observations as follows:

- The significant growth in the use of central clearing via CCPs has reduced the non-cleared market to less standard, more exotic products or products in illiquid currencies. It also means that price discovery is not centralised and trade valuation is model-based. A framework for ▶

◀ VM and IM needs to take these factors into account.

- ➔ The role of ISDA⁴ in creating a standard framework, the ISDA Master Agreement, for trading OTC derivatives, plus inclusion of the close-out netting mechanics, has been key in reducing and simplifying counterparty risk.
- ➔ The new framework will enforce the universal use of VM. Although VM has been fairly widely used, especially following the global financial crisis (GFC) of 2007–09, its use has not been universal. This regulation will mainly impact smaller counterparties as most large counterparties already post VM.
- ➔ The use of collateral for VM is one-way (towards the in-the-money counterparty). Both cash and non-cash collateral can be used, although cash is preferred as it is faster to move. VM collateral can be reused, rehypothecated and does not need to be segregated. This means that the requirement to post VM collateral does not reduce overall market liquidity.
- ➔ IM is intended to protect the non-defaulting party to a non-centrally cleared OTC trade from a loss incurred when replacing the trades due to market movements after the other party defaults, including bid-offer increases. The new framework mandates the use of IM for all non-cleared OTC derivatives. Although the concept of IM under the name ‘independent amount’ (IA) had existed previously under ISDA, its usage was not widespread.
- ➔ IM requires a two-way posting of collateral, a change in rules since current market practice has been for one-way (IA). In the event of default, the non-defaulting counterparty keeps enough of the IM collateral posted by the defaulting counterparty to cover any costs involved in replacing its trades. This is the ‘defaulter pays’ principle. It means that the amount of collateral held will exceed the potential loss to the financial system of a single counterparty default.
- ➔ IM margin collateral, which may be cash or non-cash, must be held in such a way that it would provide the non-defaulting counterparty immediate access. The WGMR defines how this collateral is to be segregated and stipulate that it cannot be rehypothecated or reused, except for strictly defined hedging purposes.
- ➔ The first approach for calculating IM is the standard schedule approach. This is based on a

schedule of ‘add-ons’ – notional weights linked to the type and maturity of each asset. Based on historical prices, we find that the add-on weights are consistent with a 10-day 99th percentile loss. However the approach is compromised by its treatment of portfolio effects which rely on the net-to-gross ratio (NGR). We examine the NGR and conclude that it does not capture diversification in the netting set. Nor does this approach take into account the moneyness of options. For this reason we find the standard schedule approach significantly overestimates the IM amount, and is misaligned to the actual risk. We cannot recommend it.

- ➔ The second WGMR approach to calculating IM is based on the use of an internal model where the IM should be the 99th percentile of the 10-day potential future exposure of the netting set. Although not a coherent risk measure, we do not consider this to be a serious criticism provided the risk-factors are Gaussian-like, which we show is the case for most of the markets covered.
- ➔ The calibration period for the IM model must be three to five years (this may differ between the EU and US regulations) and must include a period of financial stress. We believe that this may pin the period to include the GFC of 2007–09. This may narrow the scope of calibration parameters and so remove issues of pro-cyclicality that a shorter and changing calibration period could create.
- ➔ The choice of a 99th percentile embeds an estimate about the size of market movements expected following a counterparty default, and the probability the IM will cover the realised loss. We note that determining the size of the IM is difficult as there is very little empirical data for such events. We describe the events following the Lehman Brothers bankruptcy to give one example.
- ➔ We find that the WGMR modelling requirement to split the netting set by principal asset type fails to recognise the fact that many OTC derivatives have exposures to different risk types. Hence splitting by principal risk factor can penalise sensible hedging. It could be avoided by calculating the portfolio-wide IM for each risk type and summing the resulting risk type IMs.
- ➔ Two approaches to calculating the tail risk are possible. One is to assume some joint distribution whose 99th percentile can be calculated analytically. This may restrict the choice of risk factor dynamics. A more commonly used approach is to use either historical or Monte Carlo simulation. A delta-approach may be used

to speed up the calculation of IM. However given the high likelihood of non-linear products, a delta-gamma approach may be required. This may need to be checked on a case-by-case basis.

- ➔ The variety of products and pay-offs, the lack of a central price discovery venue and the need for valuation models means that disputes are likely. To minimise such occurrences we argue that as much of the model as possible should be developed via a shared industry-wide effort.
- ➔ ISDA has developed a Standard Initial Margin Model (SIMM) that is very likely to become the market standard. The ISDA SIMM model is based on the Sensitivity Based Approach which has been described by the Bank for International Settlements (BIS), a fact which may assist its regulatory approval. It avoids a Monte Carlo framework, instead applying a set of asset specific risk weights and correlations.
- ➔ The WGMR does not permit the inclusion of the modelling of both netting set and collateral in the IM calculation. In fact, EU Regulations⁵ state that the value of the collateral should not have any correlation with the netting set of derivatives. We think that this could restrict flexibility. It would perhaps make sense to incorporate collateral into the IM model as it would permit any correlations (positive or negative) between the two to be recognised.
- ➔ Differences in the implementation of the law between the US and Europe exist but do not appear to be so different that they would skew the playing field in either direction. The main difference is the exclusion of non-financial entities from the list of covered entities, and options on securities from the covered products in the US framework.
- ➔ We caveat this report with the comment that some of these regulations may be subject to change and interpretation. Readers must not rely upon this report for regulatory guidance and must consult legal and regulatory professionals.

The research from which this article was drawn was produced as part of the FBF Innovations and Regulations in Investment Banking research chair at EDHEC-Risk Institute.

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4 The International Swap and Derivatives Association (ISDA) is a trade association for OTC derivatives and their users.

5 The EU Law Supplementing Regulation No. 648/2012 on OTC derivatives.

Live is Better

Since 2013, with the Smart Beta 2.0 framework, EDHEC-Risk Institute has created Scientific Beta multi-smart-factor indices that are well diversified and exposed to rewarded factors. These indices have a robust live track record with an annualised outperformance of 2.06% compared to their cap-weighted benchmark.¹

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

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



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1 - The average live outperformance across all Scientific Beta developed regions of Scientific Beta Multi-Beta Multi-Strategy (Equal Weight and Equal Risk Contribution) indices is 2.06% and 2.20%. This live analysis is based on daily total returns in the period December 20, 2013 (live date) to December 31, 2016 for the following developed world regions – USA, Eurozone, UK, Developed Europe ex UK, Japan, Developed Asia Pacific ex Japan, Developed ex UK, Developed ex USA and Developed. The benchmark used is a cap-weighted portfolio of all stocks in the respective Scientific Beta universes.

Smart beta replication costs

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An important issue with smart beta strategies is that they typically entail higher replication costs than cap-weighted market indices. While this is obviously true, the crux of the question is not whether transaction costs are higher but whether, after accounting for such costs, there are any benefits in terms of net returns. A reasonable expectation from an investor's perspective is that providers should disclose the estimated level of transaction costs generated by their strategies so as to allow for information on net returns. However, providers typically fail to make explicit adjustments for transaction costs and satisfy themselves by reporting gross returns, leaving it to other market participants to figure out what exactly the transaction costs amount to. This article sets out to apply methods for explicit cost measurement and to thus draw conclusions on smart beta strategies.

Transaction cost estimates

Easily accessible transaction cost estimates

A first important objective of this research is to test methods which provide easy access to direct transaction cost estimates.

Transaction cost estimates for smart beta strategies are hard to obtain in practice because in principle an accurate estimation requires intraday high frequency data. One needs to observe trades and quotes within the trading day to come up with cost measures. However, not only is such data difficult to access, it is also difficult to use. The increasing frequency of trading has led to a huge amount of tick by tick price data that requires massive computational power for analysis, with some researchers arguing that the growth of high frequency equity even outpaces the growth of computing power. Moreover, tick data requires matching procedures for prices and quotes so that the quality of databases and the cleaning procedures becomes a prime concern. Moreover, high frequency data only covers relatively short time periods, making it impossible to evaluate long-term track records of smart beta strategies.

Recent research has shown that there are effective ways of estimating transaction cost variables that are only observable at high frequency, based on lower frequency (daily) data. We draw on recent advances in microstructure research to extract measures of transaction costs from daily data, such as the daily range between high and low prices and the closing bid-ask spread. Using daily data allows us to analyse longer time periods than would be possible if drawing on high frequency data. Moreover, the methods we use are not computationally intensive and they draw on easily available data, making them easily replicable for practitioners who wish to analyse smart beta strategies.

We follow two types of spread estimation methods based on daily data – one based on Corwin and Schultz (2012) who use daily

- Smart beta strategies typically entail higher replication costs than cap-weighted market indices, but the key question is not whether transaction costs are higher but whether, after accounting for such costs, there are any benefits in terms of net returns.
- Providers should disclose the estimated level of transaction costs generated by their strategies so as to allow for information on net returns, but they typically fail to make explicit adjustments for transaction costs and satisfy themselves with reporting gross returns, leaving it to other market participants to figure out what exactly the transaction costs amount to.
- The results of our research on smart beta replication costs provide an explicit estimate of costs applied to a range of strategies and show the impact of using different implementation rules or stock universes. Given the transparent methodology and benign data needs, our replication cost analysis is straightforward and can be easily applied to other strategies.

range measures such as high and low prices to estimate daily spreads (hereinafter referred to as the range-based spread estimator), and the other based on Chung and Zhang (2014) who use daily closing quoted bid and ask prices to estimate daily spreads (hereinafter referred to as the closing spread estimator).

While there is substantial literature suggesting that such measures are highly correlated with high frequency cost measures, our assessment indeed confirms that low frequency measures reliably capture the level of costs. In particular, we show that our measures capture the information content of transaction costs (effective spreads) reported by trading venues in compliance with Rule 605 regulations. They also align well with effective spreads extracted from high frequency trade and quote data (TAQ). Compared to estimates from high frequency data, our cost measures are however somewhat conservative in that they tend to slightly overestimate cost levels. This means that any conclusions about the viability of smart beta strategies in the face of transaction costs will also tend to be on the conservative side.

While we apply our cost estimates to a range of smart beta strategies to draw conclusions about cost levels, it is worth emphasising that our transaction cost measurement approach can easily be applied to testing additional strategies. Using methods such as those in this research could help the industry make cost estimates more widely available given the computational ease and widely accessible data such cost estimates are based on.

Transaction cost levels across stocks and over time

Figure 1 shows results for the average spread across all stocks, as well as the average spreads for the largest and smallest stocks in our

universe. Large and small stocks are taken as the top and bottom deciles every year by market capitalisation (as of the last trading day of the previous year). The 3,000 stocks available in every quarter of a given year are aggregated for the decile selection. The number of unique stocks may thus be greater than 3,000 in a given year. Monthly average spread estimates are then calculated for these deciles.

It should be noted that the numbers reported reflect full spreads (rather than half spreads). Therefore, the spread estimates reflect the average transaction costs for a round trip trade in the given universe of stocks.

The results suggest that both of our estimates provide similar overall results. The results also allow interesting conclusions to be drawn on the level, the time series variation, and the cross-sectional variation of transaction costs. The average spread across all stocks had frequently reached values above 2% in the 1970s, but is situated clearly below 1% in the recent part of the sample. In such an equal-weighted average across 3,000 stocks, small stocks with high spreads obviously have a high influence. When looking at the top decile (ie, the 300 largest stocks by market cap), the spread has taken on typical values in the area of 0.5% even during the early periods such as the 1970s. In contrast, the smallest decile stocks had historically reached spread levels exceeding 5%. We also observe spikes in the spread estimates which correspond to a liquidity crisis. In particular, spikes are observed in the period from late 2008 to early 2009 – a period which saw major bank failures and a drying up of liquidity.

It is worth discussing how transaction costs behaved at points when market structure changed. In the US stock market, there are a few notable points when minimum tick sizes declined. The first change occurred in 1997 when the tick size was reduced from $\frac{1}{8}$ th to $\frac{1}{16}$ th, and the second major reduction occurred in 2001 when the tick size went from $\frac{1}{16}$ th to $\frac{1}{100}$ th (ie, decimalisation). Smaller tick sizes allow for more competitive spreads. We can see that there is indeed a general reduction in spread levels if we compare the period prior to 1997 to the period after 2001.

Analysing smart beta strategies

We apply the transaction cost estimates to several smart beta strategies to draw conclusions on their implementability. For our cost estimates, we use the closing spread estimator for the period when data is available, and the range-based estimator prior to that. Our empirical analysis leads to several important conclusions in terms of replication cost estimates for smart beta strategies, which we summarise and illustrate below.

Transaction costs and implementation challenges crucially depend on the stock universe
First, we find that conclusions about transac-

tion cost levels and strategy implementation challenges are heavily dependent on the stock universe used. While it is common to see broad brush statements about investability hurdles for particular smart beta strategies, our results provide clear evidence that conclusions depend heavily on the universe under consideration. Our results on generic strategies show that cost metrics and investability metrics differ tremendously across universes.

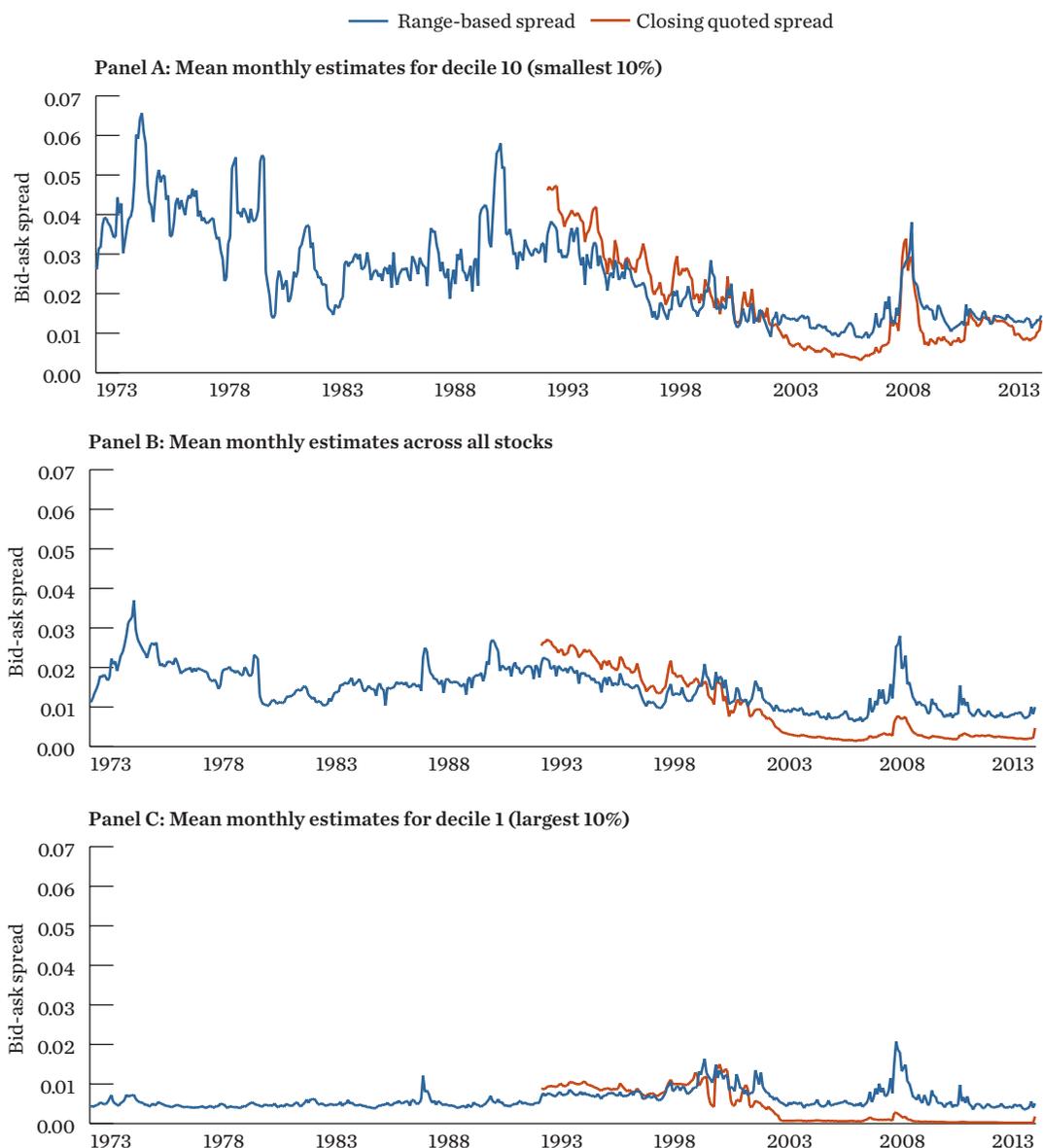
A summary of results is shown in the following exhibit. We assess different universes where we select the largest 250, 500, 1,000 and 3,000 stocks to reflect different investment universes with different levels of liquidity as a starting point for implementing smart beta strategies. We then analyse portfolios drawing on random selections from these universes to assess outcomes for different weighting schemes and universe sizes chosen. To assess generic weighting schemes, we look at market cap weighting as well as two non-cap weighted weighting schemes, namely weighting based on firm fundamentals and equal weighting (figure 2).

These results underline the dependence of implementability on the universe used as a starting point. For example, for portfolios built from the top 250 stocks by market cap, we obtain days-to-trade measures of 3.56 days for equal-weighted portfolios compared to 2.06 for the cap-weighted portfolios in the same universe. Moreover, the estimate of average annualised transaction costs is 0.13% for the equal-weighted portfolios compared to 0.04% for the cap-weighted portfolios in the same universe. When looking at portfolios formed from the broad universe (the top 3,000 stocks by market cap), we get strikingly different results. The days-to-trade measure reaches more than 100 for equal-weighted portfolios compared to about 10 for cap-weighted portfolios. Estimated transaction costs are 0.38% for equal-weighted portfolios compared to 0.05% for cap-weighted portfolios. Thus an equal-weighting strategy indeed looks extremely challenging to implement for the broad universe, but implementation measures are rather well-behaved for the large cap universe. Given such differences, it makes little sense to make statements about the investability of any given strategy per se without considering the universe it is implemented for.

Practical implementation rules effectively ease liquidity and cost issues

Our analysis provides evidence of the usefulness of practical implementation rules. Our results suggest that whether or not smart beta strategies face implementation hurdles depends on the set of implementation rules that have been included in the design. We test available index strategies by comparing them to stylised portfolios that omit the implementation rules applied in practice. Our results suggest that smart beta strategies may indeed appear challenging to implement when abstracting from commonly used implementation rules, but applying these rules leads to different conclusions. For example, we report results (see figure 3 on page 16) for a minimum volatility strategy before applying implementation rules and compare this to the same strategy after such rules have been incorporated. We show that estimated annualised transaction costs change from 0.38% to only 0.18% and investability measures such as days-to-trade go from 3.14 to 2.19 when applying practical investability rules. Perhaps more importantly, amounts traded in any stock relative to its market cap weight decline drastically from a trading multiple of 15 to a multiple of around 1. Applying

1. Effective spread estimates: top 3,000 US stock universe



The figure shows the mean monthly spread estimates based on two estimators – the Range-Based Spread Estimator and the Closing Quoted Spread Estimator. Reported spreads are mean monthly two-way spread estimates. Our sample universe consists of the 3,000 largest ordinary common stocks in the US in each quarter based on market capitalisation. As the universe is re-sampled every quarter there may be more than 3,000 stocks in a given year. The daily spread estimate of each stock is estimated based on the chosen estimator. Monthly spreads of each stock are calculated as the average of daily spread estimates of those stocks with at least 12 days of daily spread estimates in a given month. The mean monthly spreads of top decile stocks (largest 10% of stocks), bottom decile stocks (smallest 10% of stocks) based on market capitalisation and the mean monthly spreads across all stocks in our sample universe are reported for each type of estimator. Range-based spread estimates are estimated from January 1973–December 2014, and due to limited data availability closing quoted spread estimates are estimated only from January 1993–December 2014. Data source: CRSP

2. Implementation costs of generic alternative weighting schemes (US long-term track records – long term – 42 years)

US long term	Number of stocks in the universe			
31 Dec 1972–31 Dec 2014	250	500	1,000	3,000
Transaction costs				
Cap weighted	0.04%	0.04%	0.04%	0.05%
Equal weighted	0.13%	0.14%	0.17%	0.38%
Fundamental weighted	0.11%	0.12%	0.13%	0.16%
Days to trade (95 %ile)				
Cap weighted	2.06	2.39	3.79	9.99
Equal weighted	3.56	5.35	12.74	107.30
Fundamental weighted	2.48	2.93	4.80	15.13

The time period of analysis is 31 December 1972 to 31 December 2014. All statistics are annualised and daily total returns in US dollars are used for this analysis. From the 3,000 largest stocks in the US, universes comprising the 250, 500, 1,000 and 3,000 largest stocks are chosen and from each universe 1,000 random samples of 100 stocks are selected and weighted according to the generic weighting scheme chosen. Average statistics across random portfolios are reported below. Data source: CRSP, Compustat.

◀ common sense implementation rules thus reduces transaction costs and limits any stress on available trading volume.

Replication costs of practical smart beta strategies

Third, we find that for the set of indices included in our analysis, which respect a set of implementation rules, smart beta performance benefits largely survive transaction costs. When looking at commonly used smart beta indices that are built on liquid universes and integrate implementation rules, the impact of transaction costs on returns is small, far from cancelling out the relative return benefits over cap-weighted indices. Transaction costs are an order of magnitude smaller than relative returns, meaning that net relative returns do not differ materially from gross relative returns. For the three strategies we consider, namely a minimum volatility, maximum deconcentration and multi-factor index, we find that average annualised transaction costs over the 42-year period are between 0.13% and 0.18%, while gross returns relative

3. Impact of turnover and liquidity rules on minimum volatility strategy

US long term 31 Dec 1972–31 Dec 2014	Efficient minimum volatility		
	Before turnover and liquidity rules	After turnover but before liquidity rules	After turnover and liquidity rules
One-way turnover	54.57%	37.96%	30.02%
Transaction costs	0.38%	0.29%	0.18%
Days to trade (95 %ile)	3.14	3.13	2.19
Trading multiple (99 %ile)	15.53	9.64	1.30

The time period of analysis is 31 December 1972 to 31 December 2014. All statistics are annualised and daily total returns in US dollars are used for this analysis. Data source: CRSP, Scientific Beta

to the cap-weighted index range from 2.38% to 3.93%. Figure 4 shows five-year rolling window returns, both net and gross returns. For brevity, the graphs show the average return across the three strategies analysed. It is rather clear from inspecting the lines for net and gross returns that transaction costs hardly alter the returns of these strategies. However, it should be noted that such a conclusion cannot hold for smart

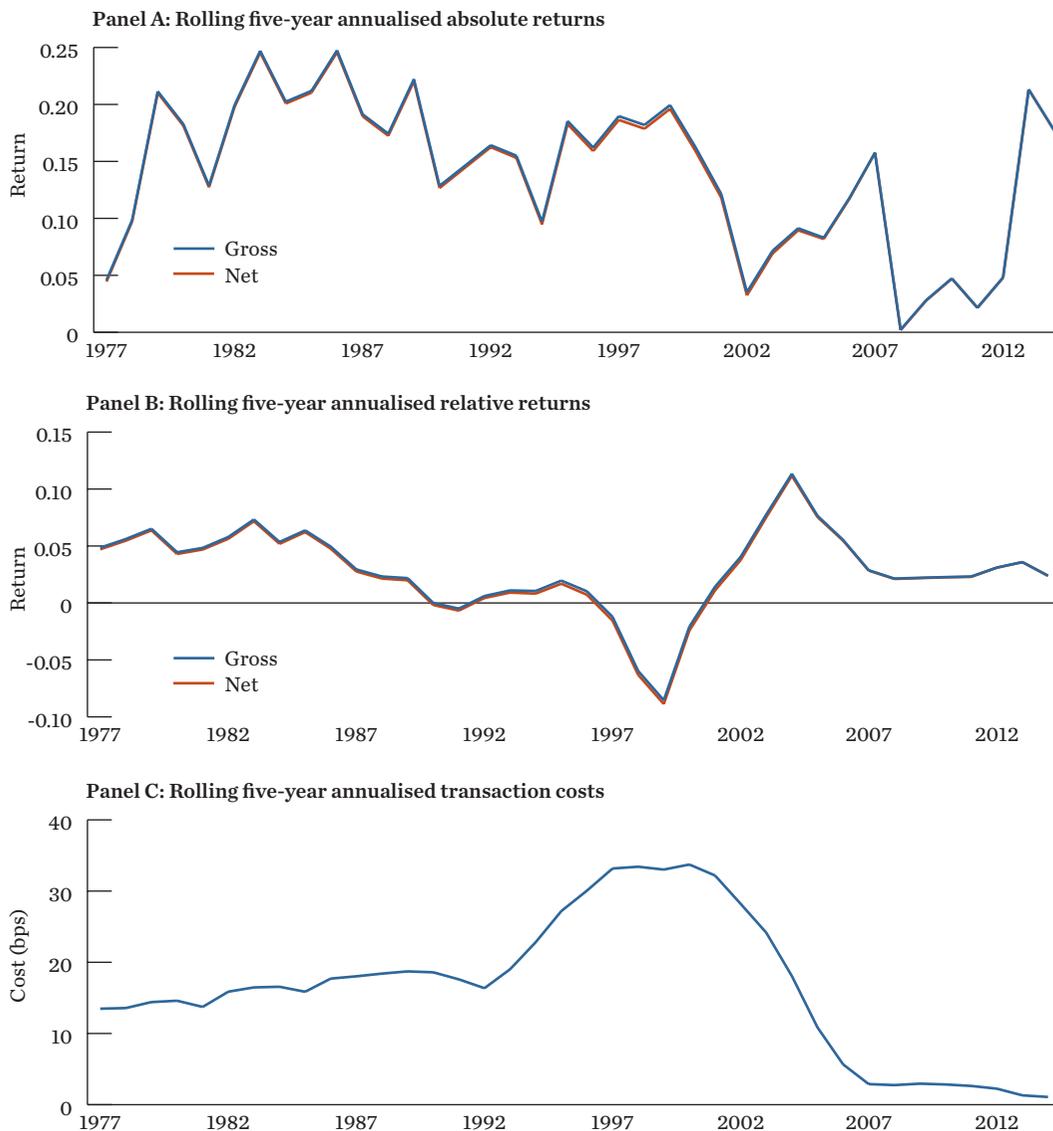
beta strategies in general, as emphasised in our first two findings. For example, with a less liquid universe or less stringent implementation rules, the same strategies may be burdened by much higher transaction cost levels and implementability issues.

Managing switching costs into smart beta strategies

Another aspect which is important to analyse is the potential cost of switching into smart beta strategies, when investors replace a currently invested portfolio with a new strategy. As a reasonable starting point from which the switch occurs, one can assume a cap-weighted portfolio based on the underlying index universe. It should be noted that investors can manage the cost of switching from cap-weighted indices to smart beta strategies in a straightforward way by stretching out the transition from a cap-weighted portfolio to a smart beta strategy. In

“Investors can manage the cost of switching from cap-weighted indices to smart beta strategies in a straightforward way by stretching out the transition from a cap-weighted portfolio to a smart beta strategy”

4. Rolling window analysis (average across three strategies: US long-term track records)



The figure presents the average annualised gross and net returns, gross and net relative returns and transaction costs of the three smart beta strategies – the SciBeta USA LTTR Efficient Minimum Volatility Index, the SciBeta USA LTTR Maximum Deconcentration Index and the SciBeta USA LTTR Multi-Beta Multi-Strategy (4-Factor) EW Index using a rolling five-year window with one-year step size. Panel A presents the gross and net absolute returns; Panel B presents the gross and net relative returns; Panel C presents the transaction costs. The average returns/costs of the three smart beta indices each year are plotted. The time period of analysis is 31 December 1972 to 31 December 2014. All statistics are annualised and daily total returns in US dollars are used for this analysis. The transaction costs estimates use the spread estimates according to the year of the rebalancing – range-based spread until 1993 and closing quoted spread from 1993 onwards. The reported transaction cost estimates are the difference between the annualised gross and net returns. Net returns are obtained after accounting for transaction costs at each quarterly rebalancing by multiplying the change in weight of each stock between the final weight before rebalancing and the optimal weights after rebalancing, including stock deletions and additions.

figure 5, we address both the transaction costs that occur through rebalancing and those that occur when initially switching from a cap-weighted index to the smart beta strategy. In order to estimate switching costs for a 10-year investment period, we apply trading cost estimates to the trades needed to switch from the cap-weighted index to the smart beta index and compute the corresponding annualised costs assuming that the switch is done for a subsequent investment period of 10 years.

It can be seen that stretching the transition over a period improves the days to trade but the returns remain almost the same. The tracking error between the stretched and non-stretched portfolios also remains quite low although they increase in the stretch period. The cost of transition is very small compared to the cost of rebalancing and the total cost is still low compared to the gross returns even after accounting for the transition costs.

Conclusions

The results of our research provide an important contribution to the analysis of smart beta strategies from a practical perspective. Indeed, the state of affairs in the evaluation of smart beta strategy performance is far from satisfying. On the one hand, strategy providers do not commonly report the transaction cost estimates of their strategies and performance evaluation

5. Comparison of stretched and non-stretched transition from cap-weighted portfolio to smart beta portfolio (long term – 42 years)

US long term 31 Dec 1972–31 Dec 2014				
	Transition	Efficient minimum volatility	Maximum deconcentration	Multi-beta multi-strategy 4-factor EW
Panel A: Transition from cap-weighted index (statistics for transition quarter)				
Days to trade (95 %ile)	Non-stretched	1.72	1.98	2.64
	Stretched 10 days	0.17	0.20	0.26
	Stretched 20 days	0.09	0.10	0.13
Tracking error	Non-stretched	–	–	–
	Stretched 10 days	0.08%	0.08%	0.09%
	Stretched 20 days	0.12%	0.11%	0.12%
Difference in gross returns by stretching	Non-stretched	–	–	–
	Stretched 10 days	0.00%	0.01%	0.00%
	Stretched 20 days	–0.01%	0.00%	–0.01%
Panel B: Cost comparison				
Annualised cost of transition from cap-weighted (assuming 10-year investment period)		0.02%	0.02%	0.03%
Annualised cost of rebalancing		0.18%	0.13%	0.17%
Total annualised cost		0.20%	0.15%	0.20%

The time period of analysis is 31 December 1972 to 31 December 2014. The strategies considered for this analysis are the SciBeta USA LTTR Efficient Minimum Volatility index, the SciBeta USA LTTR Maximum Deconcentration index and the SciBeta USA LTTR Multi-Beta Multi-Strategy (4-Factor) EW index. All statistics reported in Panel A are quarterly estimates and are averaged across all quarters. Results of three types of scenarios are estimated and presented – i) The switch from cap-weighted portfolio to smart beta portfolio happens completely on the day of rebalancing (one-day Transition); ii) The switch from cap-weighted portfolio to smart beta portfolio happens equally distributed across 10 days (10-day transition, ie, assuming only one-tenth of the portfolio switches every day for 10 days); iii) The switch from cap-weighted portfolio to smart beta portfolio happens equally distributed across 20 days (20-day transition, ie, assuming only one-twentieth of the portfolio switches every day for 20 days). Days to trade (DTT) is reported as a time-series average of the cross-sectional 95th percentile of DTT at each quarterly rebalancing. Tracking error of stretched transition (both 10 days and 20 days) over non-stretched transition is computed quarterly and average is reported. Difference in gross returns is computed quarterly between stretched (both 10 days and 20 days) transition and non-stretched transition. All statistics reported in Panel B are annualised. It compares costs of all three smart beta strategies. Assuming 10-year investment period, the annualised cost of transition from cap-weighted Index is computed as one-tenth of the immediate transition (a semi-absolute difference between weights of smart beta strategies and cap-weighted index multiplied by the average weighted spread and averaged across all quarters). Annualised cost of rebalancing is the average difference between annualised gross and net returns. Total annualised cost is sum of transition and rebalancing costs.

often relies on simulated gross returns. On the other hand, discussion of cost issues more often than not remains at the level of blanket criticism aimed at certain strategies, without considering the universe or the implementation rules that are used. Our results provide an explicit estimate of costs applied to a range of strategies and show the impact of using different implementation rules or stock universes. Importantly, given the transparent methodology and benign data needs, our replication cost analysis is straightforward and can be easily applied to other strategies.

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Measuring volatility pumping benefits in equity markets

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It has been argued that portfolio rebalancing, defined as the simple act of resetting portfolio weights back to the original weights, can be a source of additional performance. This additional performance is known as the rebalancing premium, also sometimes referred as the volatility pumping effect or diversification bonus since volatility and diversification turn out to be key components of the rebalancing premium. The rebalancing premium, intrinsically linked to long-term investing, is typically defined as the difference between the expected growth rate of a rebalancing strategy and the expected growth rate of the corresponding buy-and-hold strategy, where the portfolio growth rate is the compounded geometric mean return of the portfolio, a meaningful measure of performance in a multi-period setting.

Numerical analysis of the rebalancing premium

To set the stage for the analysis of the rebalancing premium, let us consider a universe with n assets assumed to follow a random walk, and compare a fixed-weight portfolio with regular rebalancing and the corresponding buy-and-hold portfolio considering a finite time horizon.

- We examine the argument that portfolio rebalancing, defined as the simple act of resetting portfolio weights back to the original weights, can be a source of additional performance.
- Using a selection of stocks from the S&P 500 universe we find an average historical rebalancing premium of almost 90bps (in the absence of transaction costs) for a five-year time horizon.
- Our analysis on individual stocks' characteristics highlights that size, value, momentum and volatility are sorting characteristics which have a significant out-of-sample impact on the rebalancing premium.
- The selection of small cap, low book-to-market, past loser and high volatility stocks generates a higher out-of-sample rebalancing premium compared to random portfolios for time horizons from one year to five years.

1 Where P_0 denotes the portfolio initial value and P_T its final value.

2 These weights are held constant in the rebalanced portfolio, while they drift away in the buy-and-hold portfolio.

The growth rate of a portfolio $G_p(0, T)$ on the period $[0, T]$ is defined as:¹

$$G_p(0, T) = \frac{1}{T} \ln \left[\frac{P_T}{P_0} \right]$$

If we now consider a fixed-weight portfolio P^{reb} and a buy-and-hold portfolio $P^{b&h}$ based on holding n assets with the same initial weights (w_1, \dots, w_n),² then the rebalancing premium $RP(0; t)$ over the period $[0; t]$ is simply defined by:

$$RP(0, t) = E[G_{P^{reb}}(0, t)] - E[G_{P^{b&h}}(0, t)] = E \left[\frac{1}{t} \ln \frac{P_t^{reb}}{P_t^{b&h}} \right]$$

Following Fernholz (2002) and Gabay and Herlemont (2007), we assume that the risky asset prices follow a geometric Brownian motion. Under this assumption, we can show that if all the assets have the same constant expected return then the rebalancing premium does not depend on that expected return.

We report in figure 1 the distribution probability for the excess growth rate of the rebalanced portfolio with respect to the corresponding buy-and-hold portfolio, assuming

- ◀ the following stylised base case setting in 1,000 Monte Carlo simulations:
 - ➔ The investment universe is composed by $n = 30$ risky assets;
 - ➔ The assets are uncorrelated;
 - ➔ The expected return of each asset is 10%;
 - ➔ The volatility of each asset is 20%;
 - ➔ Initial weights $w_i = 1/n$ invested in each asset;
 - ➔ The rebalancing frequency is one month;
 - ➔ The time horizon is five years.

The amplitude of the rebalancing premium, computed as the average of the excess growth rates differences in the 1,000 scenarios, is a mere 2 basis points (bps) in the base case. The distribution is negatively skewed (-0.53), the minimum difference in the 1,000 scenarios is -190bps whereas the maximum difference is 125bps. In 45% of the scenarios, the growth rates difference is between 0bps and 60bps.

We report in figure 2 the rebalancing premium for different values of the risky assets pairwise correlation (from 0% to 80%) and volatility (from 0% to 50%)³. For a given level of volatility, the rebalancing premium increases as the pairwise correlation decreases (for a constant volatility level of 40%, the rebalancing premium is 7bps if the pairwise correlation is 40% and 17 bps if the pairwise correlation is null).

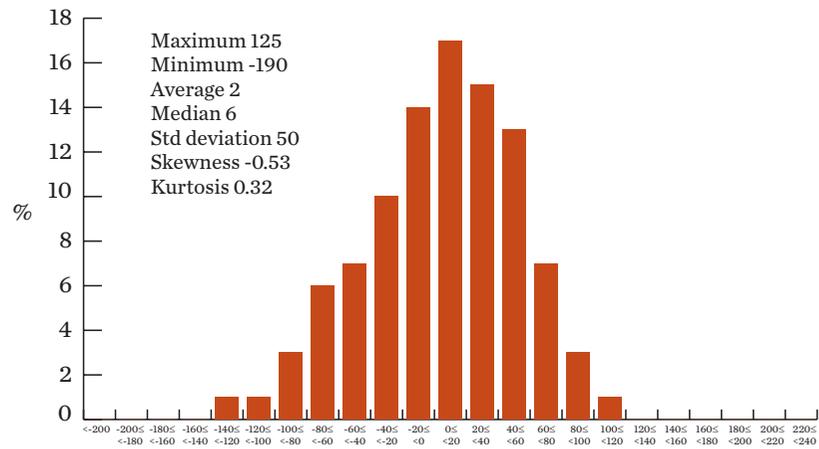
We also conduct (see Maeso and Martellini [2017] for further details) robustness checks with respect to the number of risky assets, risky asset volatility and pairwise correlation, time horizon and rebalancing frequency, and find that the rebalancing premium cannot reach values higher than 50bps for reasonable parameter values. We also document that the introduction of negative serial correlation in asset returns via a fractional Brownian motion substantially enhances the amplitude of the rebalancing premium.

Empirical analysis of the rebalancing premium

Since this controlled numerical analysis cannot shed insights regarding the actual size of the rebalancing premium that can be harvested in practice, we then provide an empirical analysis of the rebalancing premium in realistic settings. The base universe of our empirical study consists of the 132 stocks extracted from CRSP which have continuously been in the S&P 500 index from November 1985 to December 2015. While this obviously implies the presence of a survivorship bias in equity portfolio performance, there is no reason to assume that it will impact the main comparative results of our analysis. We use a resampling procedure and build one set of 30 randomly selected equally-weighted portfolios and another set with the 30 randomly selected corresponding buy-and-hold portfolios. Then we average the (historical) rebalancing premium for the two sets of 30 random sets of portfolios. More precisely, the rebalancing premium that we use to compare the rebalanced portfolios with the buy-and-hold portfolios is reported in this setting as the average of the rebalancing premium over the 30 random portfolios. This particular procedure mitigates the impact of stock selection biases. We consider the following set of values for the number of stocks in each randomly selected universe: 2, 10, 30, 50 and 132. In the case where we take $N = 132$, which is equal to the total size of the universe under analysis, we of course obtain a single portfolio, as opposed to 30 different portfolios.

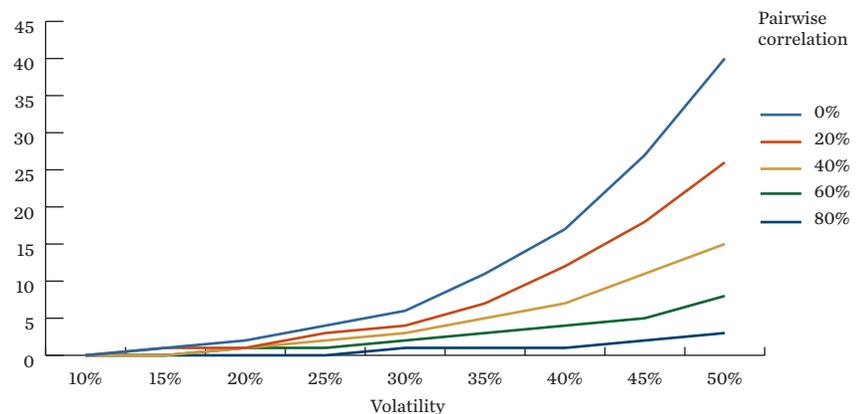
We make the following assumptions: (i) the initial weight invested in each asset is $w_i = 1/N$ and (ii) the rebalancing frequency is one month. Firstly, we focus in figure 3 on the historical

1. Distribution of the growth rates difference (bps)



This figure displays the probability distribution of the difference between the growth rate of the rebalanced portfolio and that of the corresponding buy-and-hold portfolio in the numerical base case for an investment universe made of 30 risky assets. The time horizon is five years.

2. Rebalancing premium for an investment universe made up of 30 risky assets (bps)

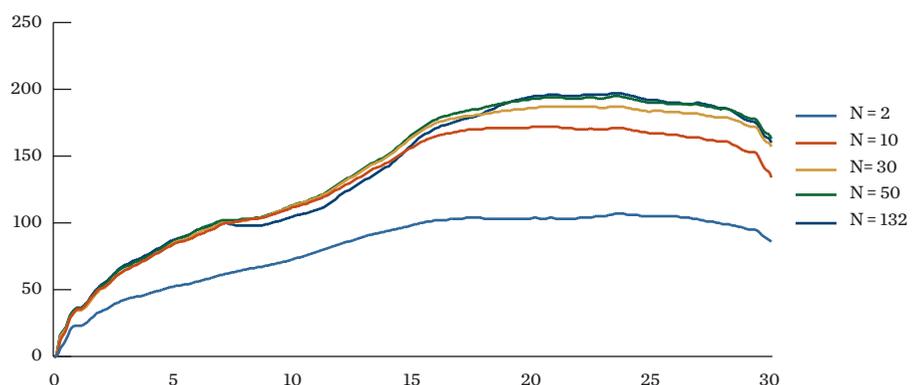


This figure displays the rebalancing premium (in bps) as a function of the volatility of the risky assets for different values of the pairwise correlation for an investment universe made up of 30 risky assets. The rebalancing frequency is one month and the time horizon is five years.

rebalancing premium as a function of time horizon (ranging from one month to 30 years) for different numbers of stocks in the portfolios. For a five-year time horizon and a number $N = 30$, the historical rebalancing premium is reasonably high at 85bps. In a different configuration, with a 10-year time horizon and $N = 50$ risky assets, the historical rebalancing premium is 113bps. We assess that the number of stocks considered has almost no influence as long as it

exceeds a minimum value around 10. This first perspective shows that the historical rebalancing premium from our S&P 500 base universe is higher than 50bps if the number of stocks N is higher than or equal to two and time horizon is at least five years. If we take the number of stocks N higher than or equal to 10, then the historical rebalancing premium is higher than 50bps for time horizons higher than or equal to two years.

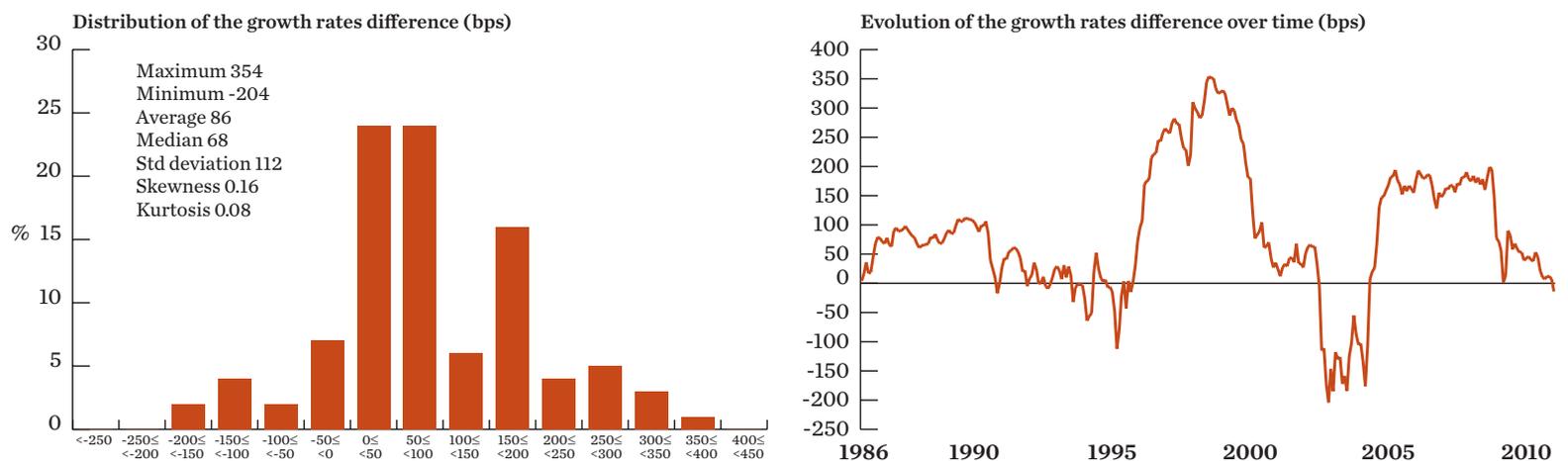
3. Historical rebalancing premium (bps)



This figure displays the historical rebalancing premium (in bps) as a function of the time horizon (in years) considered for different number of stocks in the portfolios.

³ All the other parameters stay unchanged.

4. Historical distribution of the growth rates difference (bps)



This figure displays the distribution of the average (across random portfolios) difference between the realised growth rate of the rebalanced portfolios and that of the corresponding buy-and-hold portfolios. The time horizon considered is five years and the number of stocks in the portfolios is $N = 50$. It also displays the evolution of the five-year average (across random portfolios) growth rates difference over time.

Figure 4 shows the distribution of the difference in growth rates for a five-year time horizon and also displays the evolution of that difference over time for the period November 1985–December 2010. Each date on this chart corresponds to a five-year period starting date. The analysis of the five-year realised growth rates difference allows us to have a more precise view on all the five-year historical scenarios and not only their average. The average growth rates difference, ie, the historical five-year rebalancing premium, is 86bps. The growth rates difference achieves the highest value (higher than 100bps) for the starting dates in the period January 1996–January 2000 and August 2004–October 2008, and the lowest value (lower than -50bps) for the starting dates in the period July 2002–March 2004. We note that among the 302 historical five-year scenarios, 36% of them display a growth rates difference higher than 100bps, 61% display a growth rates difference higher than 50bps and 16% display a negative growth rates difference. Overall, these results suggest that the rebalancing premium can be substantial in equity markets.

Rebalancing premium and stocks' characteristics

The objective of this section is to determine whether the rebalancing premium differs for various groups of stocks. To see this, we test for the empirical relationship between the (out-of-sample) historical rebalancing premium and standard characteristics such as market capitalisation, book-to-market ratio, past performance, volatility and serial correlation. We are also interested in the persistence of the criteria used in the stock selection process since it is only if the characteristic is persistent that investors could benefit from tilting their portfolio towards that particular characteristic in an attempt to increase the rebalancing premium.

We still consider the 132 stocks which were in the S&P 500 over the period November 1985–December 2015 as our base universe and take five possible time horizons: one, two, three, four and five years. We do not consider longer horizons for a persistence criterion.

For a given characteristic (market capitalisation for instance) we build at each initial (end-of-month) date t_0 two sets (one 'high' and one 'low') of two portfolios (one equally-weighted and one buy-and-hold):

- ➔ The first set of portfolios ('high') is made up of the 30 best-performing stocks of the base

universe according to the characteristic at the initial time;

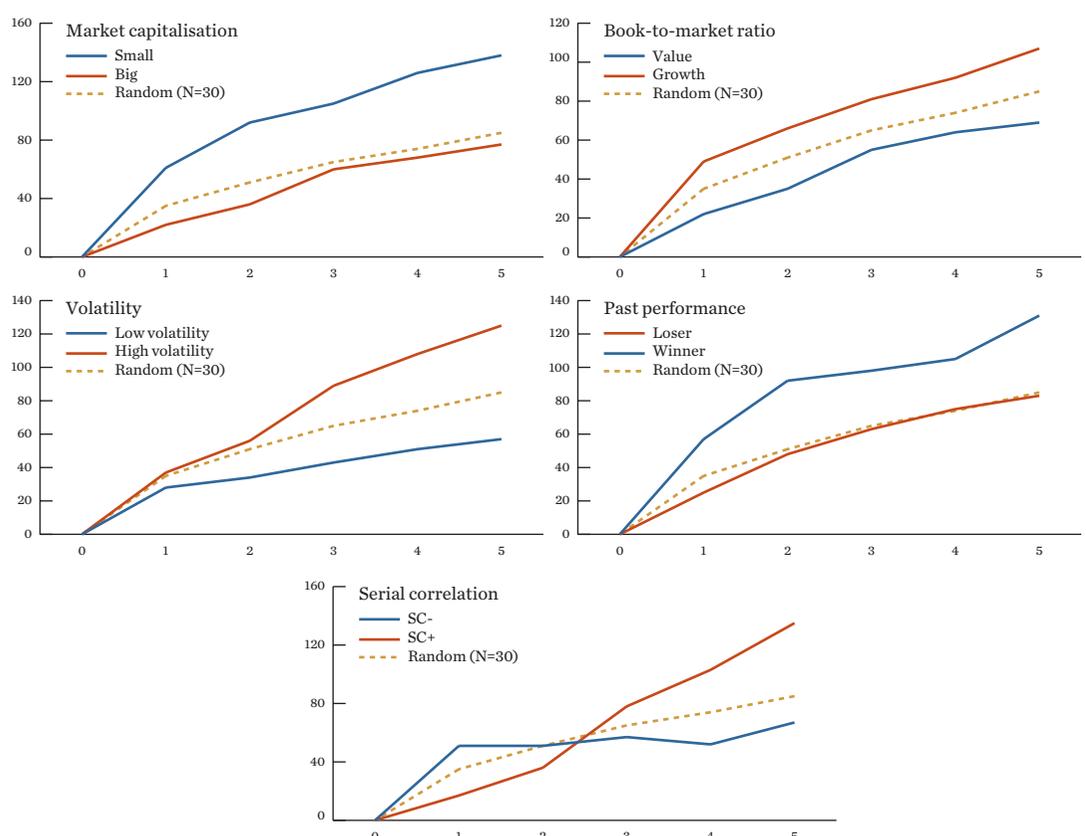
- ➔ The second set of portfolios ('low') is made up of the 30 worst-performing stocks of the base universe according to the characteristic at the initial time.

The investment universe for each portfolio is held constant over the corresponding time-horizon, which allows us to analyse the influence of the characteristic on the volatility pumping effect. We then compute for each characteristic and each time horizon the average rebalancing premium of the 'high' and 'low' sets. We compare the 'high' and 'low' sets to a set of

portfolios built randomly with 30 stocks of the base universe. This approach allows us to see if the characteristic has an impact on the rebalancing premium.

We assess in figure 5 that market capitalisation, book-to-market ratio, past performance and volatility are sorting characteristics that have a significant impact on the rebalancing premium. Small cap, growth, past loser and high volatility portfolios display respective out-of-sample five-year rebalancing premiums of 138, 107, 131 and 125bps when random portfolios ($N = 30$) display on average a five-year rebalancing premium of 85bps. The five-year rebal-

5. Historical rebalancing premium (bps) with market capitalisation, book-to-market ratio, volatility, past performance and serial correlation as sorting characteristics



This figure displays, for different characteristics, the historical rebalancing premium (in bps) as a function of the time horizon (in years) when portfolios are sorted by corresponding characteristic of the stocks (blue lines and red lines). The characteristics tested are market capitalisation, book-to-market ratio, volatility, past performance and serial correlation. We also display the rebalancing premium (orange dashed lines) when the $N = 30$ stocks are randomly selected from the base S&P 500 universe. The time horizons considered are one, two, three, four and five years.

Not All Value Indices are Equal... Some are Smart

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

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

With annual outperformance of 2.67% since the base date compared to MSCI World¹ and annual live outperformance of 1.13% compared to MSCI World Value,² the Scientific Beta Developed Value Diversified Multi-Strategy index is unquestionably a smart opportunity to invest in the Value factor.

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



www.scientificbeta.com

1 - The annualised relative return since the base date compared to MSCI World for the Scientific Beta Developed Value Diversified Multi-Strategy index as of December 31, 2016, is 2.67%. Analysis is based on daily total returns in USD from June 21, 2002 to December 31, 2016. The base date is June 21, 2002 for the Scientific Beta Developed Value Diversified Multi-Strategy index. MSCI World is used as the benchmark. All statistics are annualised.

2 - The annualised relative return since live date compared to MSCI World Value for the Scientific Beta Developed Value Diversified Multi-Strategy index as of December 31, 2016, is 1.13%. Analysis is based on daily total returns in USD from December 21, 2012 to December 31, 2016. The live date is December 21, 2012 for the Scientific Beta Developed Value Diversified Multi-Strategy index. MSCI World Value is used as the benchmark. All statistics are annualised. MSCI® is a registered trademark of MSCI Inc.

ancing premium can be enhanced by more than 40bps if stocks are selected according to a characteristic such as market capitalisation rather than randomly. On the other hand serial correlation as a sorting characteristic does not lead to a substantially higher rebalancing premium for time horizons higher than one year: for instance the five-year rebalancing premium for portfolios of stocks with negative serial correlation is 67bps. This result suggests the presence of a relative lack of persistence of serial correlations at the individual stock level.

Conclusion

Using a selection of stocks from the S&P 500 universe we find an average historical rebalancing premium of almost 90bps (in the absence of transaction costs) for a five-year time horizon. Our analysis on individual stocks' character-

istics highlights that size, value, momentum and volatility are sorting characteristics which have a significant out-of-sample impact on the rebalancing premium. In particular, the selection of small cap, low book-to-market, past loser and high volatility stocks generates a higher out-of-sample rebalancing premium compared to random portfolios for time horizons from one year to five years. Taken together, these results suggest that a substantial rebalancing premium can be harvested in equity markets over reasonably long horizons for suitably selected types of stocks.

While our analysis has focused on an individual stock universe, it could be usefully applied to various equity benchmark portfolios such as style, sector, factor or country indices. The analysis of the volatility pumping effect may also be transported beyond the equity universe, either

in a bond portfolio context or in a multi-asset context. Once a deep understanding of how to most efficiently harvest the rebalancing premium has been obtained, we could also focus on how to transport these benefits in a portfolio context. In particular, one would like to analyse the conditional performance of the rebalancing premium harvested within and across asset classes so as to better assess its diversification benefits.

The research from which this article was drawn was supported by BdF Gestion.

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Introducing a multi-beta diversified max factor exposure strategy

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

There are two approaches to factor investing. The first approach is a diversification strategy where the main objective is to maximise the index's diversification power while controlling the factor exposures. This strategy corresponds to Scientific Beta's existing Multi-Beta Multi-Strategy offering. This control of factor exposure is not synonymous with maximal factor exposure since the primary objective is diversification. The second approach is an efficient strategy to maximise the benefit of the exposure to long-term rewarded factors. In this case, diversification of specific risk is not an objective but a way in which to extract the factor premia efficiently. This strategy is part of our Multi-Beta Multi-Strategy Solutions offering, which aims to meet an investor's particular objective, which here will be maximisation of the factor exposure.

Geometric mean score

The solution is based on a top-down approach that implements dynamic allocation between smart factor indices. This allocation is guided by a method that aims to maximise the geometric mean score across factors while preserving a certain balance between the factor exposures. The choice of geometric mean maximisation as opposed to arithmetic mean is grounded in the fact that the geometric mean approach will result in more balanced exposures. Maximisation of the arithmetic mean can severely penalise one factor score over another in an attempt to attain a higher average score. The objective of the maximum geometric score approach is to maximise the overall multi-factor score while respecting individual factor constraints, ie, each factor score is greater than the median score.

Top down score maximisation

The geometric score maximisation method is expected to result in equilibrium in the six

- We introduce a new ERI Scientific Beta approach with the objective of maximising exposure to the long-term rewarded factors in a 'top-down' framework, in a robust and well-diversified manner.
- Scientific Beta's Multi-Beta Diversified Max Factor Exposure index dynamically allocates across single-factor indices in order to retain diversification benefits and obtain maximum exposure while maintaining balance across factors and reasonable diversification levels.
- Compared to allocations focusing mostly on diversification rather than factor exposure objectives, the index achieves higher factor intensity and more balanced exposure to individual factors, but it comes with higher idiosyncratic risk and higher tracking error, as well as with higher level of turnover.
- The Diversified Max Factor Exposure approach corresponds to a particular investor objective which is to have high factor intensity. However, the 'top-down' framework, in which dynamic allocation is implemented, is flexible in a sense that factor objectives can be interpreted in a straightforward manner, and can be fitted to a broad range of investor preferences.

factor exposures. However, aggregating the component level geometric scores in this way does not seem to make a lot of sense. A simple example shows this (figure 1).

A weighting by geometric score would lead to a 100% weight in stock 3 and a portfolio score

of 0.01. However, holding 50% in stock 1 and 50% in stock 2 leads to a geometric score at the portfolio level of 0.25 – a much higher score. To avoid these problems of sub-optimality in the use of geometric scores, we propose to integrate them into an optimisation function (maximisation).

However, some practitioners employ 'bottom-up' approaches and construct portfolios based on stock level composite scores, such as arithmetic or geometric average of all factor scores. Contrary to this, we maximise geometric average score by allocating to well-diversified high factor exposure indices that we discuss in more detail in the next subsection. Looking at average scores on an index level rather than stock level not only avoids the problem discussed previously, but also avoids security-level noise and results in better diversification compared to 'bottom-up' approaches. Amenc et al (2017) provide detailed comparison of these two approaches.

High factor exposure indices

To facilitate this allocation and guarantee a good multi-factor exposure capacity, it is proposed that new multi-factor allocation supports be used, namely single smart factor indices representative of the selected weighting strategies, but that take account of the stocks' residual exposures. For this reason, high factor exposure (HFE) filtered indices are used as ingredients for allocation. In this 'top-down' allocation approach, it is possible to rely on well-diversified building blocks as a starting point, ►

1. Example of aggregating geometric scores

Constituent	Value score	Momentum score	Geometric score
Stock 1	0	1	0
Stock 2	1	0	0
Stock 3	0.1	0.1	0.01
EW portfolio of stock 1 and stock 2	0.5	0.5	0.25

◀ which is a key difference with ‘bottom-up’ approaches which concentrate in factor champion stocks. Moreover, a ‘top-down’ approach allows for straightforward control of particular factor exposures while concentrated ‘bottom-up’ approaches are unable to control particular factor exposures as they are solely guided by the characteristics of champion stocks. If the stocks with the highest composite score tend to be highly exposed to a given factor (such as value or low volatility) in a particular period, concentrated ‘bottom-up’ approaches will not be balanced across factors. On the other hand, within a ‘top-down’ framework, one can address this issue by employing suitably designed diversification constraints and exposure constraints on individual factors.

The HFE filtered approach aims at taking into consideration the cross section of factor exposures at stock level to reduce strong negative exposure of stocks to the factors that are not targeted in the selection, as discussed in detail in the accompanying article ‘Improving multi factor exposure without sacrificing diversification and risk control’ (see page 24). The single factor strategy indices which are used here are constructed on these HFE selections.

Allocation methodology

Ingredients

The allocation is performed across 25 tilted HFE single strategy indices (mono indices). For each of the following five tilts, the following five weighting schemes are applied:

- ➔ Value, high momentum, low volatility, high profitability, low investment;
- ➔ Maximum deconcentration, maximum decorrelation, efficient minimum volatility, efficient maximum Sharpe, diversified risk weighted.

Mid-cap tilted indices are not included in the list because the mid-cap tilt, relative to broad cap weighting, is implicitly present in the other factor-tilted indices. This is because the five weighting schemes used on each factor tilt deconcentrate the portfolio relative to cap weighting and in doing so overweight smaller stocks.

Scoring

We observe K attributes in the cross section of U stocks. We assign numeric ranks to all the observations, beginning with 1 for the smallest (largest) value for attributes associated with positive excess returns (negative for stocks that have attribute values associated with negative excess returns).

With $b_{i,k}$ the k-th attribute of the i-th stock, we can conveniently standardise the attribute values by calculating ranks as

$$c_{i,k} = \frac{\text{rank}(b_{i,k})}{U} .1$$

Further there are N indices composed of these stocks, and for the j-th index and the weighted average k-th attribute is:

$$c_{j,k} = \sum_{i=1}^U w_{j,i} c_{k,i}$$

where $w_{j,i}$ denotes the weight of stock i in index j. We can now construct a portfolio which combines the indices and the k-th weighted

average portfolio attribute as follows (where $w_{p,j}$ denotes the weight of index j in the final portfolio/‘solution’):

$$c_{p,k} = \sum_{j=1}^N w_{p,j} c_{j,k}$$

Optimisation problem

Maximum geometric mean score (Max GMS) optimisation is performed with a constraint on factor scores and deconcentration. All six factor scores are constrained to be greater than the median score (0.50). Norm constraints are applied simultaneously to ensure deconcentration across ingredients. The effective number of constituents is at least N/3, where N is the total number of constituents. N is 25 when 25 mono indices are used.

$$w^* = \text{argmax} [C_{P,SMB}^{1/6} * C_{P,HML}^{1/6} * C_{P,MOM}^{1/6} * C_{P,VOL}^{1/6} * C_{P,PRF}^{1/6} * C_{P,INV}^{1/6}]$$

$$C_{p,k} \geq 0.50 \forall k \in [SMB, HML, MOM, VOL, PRF, INV]$$

$$\frac{1}{\sum w^2} \geq \frac{N}{3}$$

The constraint on the effective number of constituents corresponds to a typical decon-

centration constraint which ensures that the solution to the portfolio optimisation will not result in a portfolio which is very concentrated in few constituent indices. The constraint on each factor exposure ensures that the resulting allocation will not obtain lower than average exposure for any given factor thus avoiding drastic imbalances in exposures across factors. The allocations are rebalanced semi-annually on the third Friday of June and December.

Performance and risk

So far, we have seen how maximising the geometric mean of scores effect individual factor scores. We now turn to the assessment of the performance, risk and factor exposures of diversified max factor exposure along with portfolios that allocate equal weights to both standard factor-tilted indices and those with the high factor exposure filter, and make comparison with the cap-weighted index. While maximisation of factor scores is done at a cost of diversification, and is expected to incur additional turnover at the same time, we also look at diversification and investability measures in figure 2.

2. Performance and risk

US long term track record

31 Dec 1975–31 Dec 2015	Broad cap-weighted	Multi-beta multi-strategy diversified max factor exposure	Multi-beta multi-strategy high factor exposure (HFE multi-beta multi-strategy EW 6F)	Multi-beta multi-strategy diversification (multi-beta multi-strategy EW 6F)
Annualised returns	11.12%	14.89%	14.79%	13.98%
Annualised volatility	17.04%	13.88%	13.91%	15.18%
Sharpe ratio	0.36	0.72	0.71	0.59
Maximum drawdown	54.31%	48.27%	48.69%	52.59%
Annualised relative returns	–	3.77%	3.67%	2.86%
Annualised tracking error	–	6.39%	5.80%	4.39%
Information ratio	–	0.59	0.63	0.65
Outperformance probability (3Y)	–	79.81%	81.26%	79.09%
Extreme relative return (5%-ile)	–	–9.26%	–8.37%	–6.92%
Extreme tracking error (95%-ile)	–	12.66%	10.87%	8.33%
Maximum relative drawdown	–	41.60%	36.63%	30.34%
Annualised unexplained	0.00%	1.77%	1.92%	1.38%
Market beta	1.00	0.97	0.97	1.00
SMB beta	0.00	0.18	0.18	0.19
HML beta	0.00	0.18	0.14	0.12
MOM beta	0.00	0.06	0.04	0.04
Low volatility beta	0.00	0.12	0.14	0.06
High profitability beta	0.00	0.08	0.09	0.05
Low investment beta	0.00	0.13	0.07	0.05
R-squared	100.00%	93.33%	94.29%	95.98%
Factor intensity	0.00	0.75	0.66	0.51
Factor imbalance	–	37.76%	42.15%	64.04%
Factor drift	–	0.22	0.21	0.19
Factor intensity drift	–	30.36%	28.96%	39.19%
Geometric mean score	0.44	0.59	0.58	0.54
Annualised one-way turnover	2.42%	56.98%	34.18%	29.96%
Capacity (\$m)	52,284	12,622	13,205	12,909
Effective number of stocks	122	153	195	333
GLR measure	25.76%	20.64%	20.21%	19.41%
Idiosyncratic risk	–	3.57%	3.31%	3.01%
Residual Sharpe ratio	–	0.49	0.58	0.46
Volatility reduction compared to multi-factor benchmark	–	–2.73%	–3.24%	–2.62%

The analysis is based on daily total returns in US dollar over the 40-year period from 31 December 1975 to 31 December 2015. All statistics are annualised. Return on secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. Maximum relative drawdown is the maximum drawdown of the long/short index whose return is given by the fractional change in the ratio of strategy index to the benchmark index. Probability of outperformance is the probability of getting positive relative 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 is used. The regressions are based on weekly total returns. The market factor is the excess return series of the cap-weighted index over the risk-free rate. Other factors are constructed from the return series of long/short portfolios formed by equally weighting stocks in the top/bottom three deciles of ranks for each factor criterion. Figures in bold correspond to p-values of 5% or less. Factor intensity is the sum of all betas except market beta. Factor imbalance (RMSE) is the root mean squared error of factor betas with respect to the average beta. Factor drift is the square root of the sum of factor exposure variances excluding the market beta. Factor intensity drift is the standard deviation of factor intensity per unit of factor intensity. The reported turnover and capacity numbers are averaged across 160 quarters. Volatility reduction is measured as the difference between the volatility of the strategy and its multi-factor benchmark, which is a synthetic portfolio, levered to match returns of the respective strategy, and contains an exactly similar magnitude of systematic risk. The GLR measure is the ratio of the variance of a portfolio's returns to the weighted average of the variance of its constituents' returns. The residual Sharpe ratio is unexplained return per unit of idiosyncratic risk, which is the standard deviation of residuals from the seven-factor regression.

1 To reduce the variability in scores affecting the robustness of optimisation, we can adopt the deciles technique in scoring that we already use in maximum Sharpe ratio optimisation. The idea is to sort the stocks into deciles by their factor scores, then assign all stocks in a given decile the median score of that decile. This adjustment scoring is done at building block level, ie, when the scores are assigned. This only affects the stock level scores.

In figure 2, if we compare multi-beta multi-strategy diversified high factor exposure (HFE MBMS-EW 6F) and multi-beta multi-strategy diversification (MBMS-EW 6F) allocations it becomes clear that HFE filtering improves the overall outperformance of multi-beta allocations as it removes stocks that are negatively exposed to other factors, which is beneficial from the point of view of long-term performance. The risk-adjusted performance, ie, the Sharpe ratio, also shows improvement as it goes from 0.59 to 0.71 over the 40-year period. The most remarkable improvement, which is also a direct result of HFE filtering, is the improvement in factor betas. Low volatility and high profitability betas increase by a substantial amount, and HML and low investment betas increase moderately. As a result, the factor intensity, which is the sum of the six factor betas, goes from 0.51 to 0.66. Another improvement worth mentioning is that accounting for cross-factor interactions effectively reduces imbalance between factor exposures from 64% to 42%.

The multi-beta multi-strategy diversified max factor exposure allocation aims to further improve the factor exposure compared to the multi-beta multi-strategy diversified high factor exposure (HFE MBMS-EW 6F) allocation. The average geometric mean score of this allocation is 0.59 compared to 0.58 for the multi-beta multi-strategy diversified high factor exposure (HFE MBMS-EW 6F) allocation and 0.44 for the broad cap-weighted index. A gain in factor intensity is also observed, from 0.66 to 0.75. In line with the allocations and scores discussed previously, most of the factor intensity improvement is due to the gains in value and low investment betas. As desired, the factor betas of this allocation are more evenly spread out. However, the benefits from maximising factor exposure do not come without costs. Since the main objective of the allocation is not diversification, we can observe higher idiosyncratic risk and more than 1.5 times higher turnover for the diversified max factor exposure allocation compared to diversified high factor exposure. As expected, concentration also increases since the effective number of stocks decreases from 195 to 153.

Another advantage of 'top-down' approaches in multi-factor portfolio construction is high stability of both individual factor exposures and factor intensity. These results are consistent across all multi-beta indices. As we can see in figure 2, factor drift, which we compute in a similar way to the style drift measure of Idzorek and Bertsch (2004), and which reflects the total instability of individual factor exposures, is in the order of 0.2. Factor intensity drift is also on average 33% relative to the average intensity across time. The same measures for the portfolios based on the 'bottom-up' approach are significantly higher, as documented in Amenc et al (2017).

Emphasising a particular factor within diversified max factor exposure approach: the case of value

A key advantage of the top-down approach is

3. Illustration of targeting higher value exposure

US long term track record			
31 Dec 1975–31 Dec 2015	Broad cap-weighted	Multi-beta multi-strategy diversified max factor exposure targeting higher value score (0.625)	Multi-beta multi-strategy max factor exposure
Annualised returns	11.12%	14.95%	14.89%
Annualised volatility	17.04%	13.99%	13.88%
Sharpe ratio	0.36	0.71	0.72
Maximum drawdown	54.31%	48.97%	48.27%
Annualised relative returns	–	3.83%	3.77%
Annualised tracking error	–	6.27%	6.39%
Information ratio	–	0.61	0.59
Outperformance probability (3Y)	–	80.07%	79.81%
Extreme relative return (5%-ile)	–	–9.41%	–9.26%
Extreme tracking error (95%-ile)	–	12.67%	12.66%
Maximum relative drawdown	–	41.51%	41.60%
Annualised unexplained	0.00%	1.86%	1.77%
Market beta	1.00	0.97	0.97
SMB beta	0.00	0.17	0.18
HML beta	0.00	0.22	0.18
MOM beta	0.00	0.06	0.06
Low volatility beta	0.00	0.11	0.12
High profitability beta	0.00	0.12	0.08
Low investment beta	0.00	0.08	0.13
R-squared	100.00%	93.55%	93.33%
Factor intensity	0.00	0.76	0.75
Factor imbalance	–	43.02%	37.76%
Factor drift	–	0.22	0.22
Factor intensity drift	–	30.26%	30.36%
Geometric mean score	0.44	0.59	0.59
Annualised one-way turnover	2.42%	54.41%	56.98%
Capacity (\$m)	52,284	12,574	12,622
Effective number of stocks	122	158	153
GLR measure	25.76%	20.69%	20.64%
Idiosyncratic risk	–	3.54%	3.57%
Residual Sharpe ratio	–	0.53	0.49
Volatility reduction compared to multi-factor benchmark	–	–2.97%	–2.73%

The measures reported are the same as those in figure 2.

that factor exposure objectives can be considered in a straightforward manner. We illustrate this by increasing the lower bound on the value score at a level that is 25% higher than the base case (ie, 0.625 instead of 0.5). As can be observed from figure 2, introducing a target of stronger value exposure effectively allows the value exposure to be increased from 0.18 to 0.22. Unsurprisingly, this leads to slightly higher imbalance between factor exposures, but individual factors, as well as intensity, stays as stable as they were before, as there is no increase in Factor Drift or Factor Intensity Drift. Moreover, investability measures such as turnover and capacity do not change and we are able to retain a high level of diversification.

Conclusion

Achieving high factor exposure may not be a suitable objective for everyone because it goes against diversification and requires higher turnover. A standard multi-beta multi-strategy

diversification (MBMS-EW 6F) solution without HFE filtering is naturally more diversified than a multi-beta multi-strategy diversified max factor exposure solution that uses HFE filtered indices. Our approach of maximising the overall factor exposure by allocating across indices which themselves remain well diversified is a way of addressing a strong factor exposure objective in a robust and well diversified manner while avoiding the overconcentration of score weighting approaches, which emphasise stock-level differences which are subject to a lot of noise.

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Improving multi-factor exposure without sacrificing diversification and risk control

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In light of increasing investor interest in multi-factor solutions, product providers have recently been debating the respective merits of the ‘top-down’ and ‘bottom-up’ approaches to multi-factor portfolio construction. ‘Top-down’ approaches assemble multi-factor portfolios by combining distinct sleeves for each factor, while the ‘bottom-up’ methods build multi-factor portfolios in a single pass by choosing and/or weighting securities by a composite measure of multi-factor exposures. In this article, we discuss the results of recent research assessing the merits of both approaches.

‘Top-down’ multi-factor portfolios blend single factor portfolios with a view to drawing on differentiated sources of returns while reducing the conditionality of performance. The approach is simple and transparent and affords flexible factor-by-factor control of multi-factor allocation, which makes it possible to serve diverse needs through different combinations of the same building blocks and, more importantly, allows for dynamic strategies. Its tractability and granularity also facilitate performance analysis, attribution and reporting. Being typically assembled from reasonably diversified factor sleeves, ‘top-down’ multi-factor portfolios tend to result in portfolios with large effective numbers of stocks and thus good diversification of idiosyncratic risk.

‘Bottom-up’ portfolio construction has been favoured by practitioners seeking to concentrate portfolios to offer higher scores across targeted factors with a view to reaping the higher rewards expected from higher exposures. Indeed, under reasonable assumptions about the mapping of factor scores by securities, the direct selection and/or weighting of securities on the basis of their characteristics across the targeted factors will result in higher factor scores than the combination of specialised sleeves can achieve. The difference in potential scores between the two approaches increases with the targeted concentration of the portfolio and the number of factors targeted and decreases with factor correlations. While this is a general problem, the superiority of ‘bottom-up’ over ‘top-down’ approaches for the achievement of high scores across multiple factors is typically illustrated by examples involving a pair of factors with low correlation such as valuation and momentum. Mixing stand-alone portfolios targeting a high score for one factor in isolation leads to holding securities with low or negative scores in respect of the other targeted tilt. These securities that cause accelerated dilution of the scores of targeted tilts within the total portfolio can be avoided altogether when the two-factor portfolio is built directly by choosing securities

- Concentrated bottom-up multi-factor indices that focus solely on increasing factor intensity face several challenges, but suitably designed top-down approaches are able to account for cross-factor interactions while avoiding such challenges.
- Concentrated bottom-up indices are inefficient in capturing factor premia, as exposure to unrewarded risks more than offsets the benefits of increased factor scores. High factor scores in ‘bottom-up’ approaches also come with high instability and high turnover.
- Cross-factor interactions can be taken into account in ‘top-down’ portfolios through an adjustment at the stock selection level using Scientific Beta’s high factor exposure approach. The approach dominates concentrated ‘bottom-up’ approaches in terms of relative performance and excess returns per unit of factor intensity, while considerably reducing extreme relative losses and turnover.

that score highly in respect of each factor or on average across the two factors.

Proponents of ‘bottom-up’ approaches argue that their higher factor exposures produce additional performance that makes it worthwhile for most investors to forsake the simplicity, transparency and flexibility of ‘top-down’ approaches. However, while studies of ‘bottom-up’ approaches such as the one by Bender and Wang (2016) document increased long-term returns, they typically fail to discuss short-term risks, and implementation issues such as heightened turnover.

More generally, the question of the superiority of the ‘bottom-up’ approach should be addressed from the perspective of the robustness and investability of the performance displayed in-sample. Ultimately, investors are interested not in attractive-looking simulated track records but in true performance that is replicable out-of-sample. For ERI Scientific Beta, one of the keys to this robustness is the support of consensual, non-vested academic research.

It is understandable that computational technicians will have a tendency to aim at accounting for stock level exposures to multiple factors with the highest possible precision; it is worth considering insights from finance. Empirical evidence on factor premia overwhelmingly suggests that the relations between factor exposures and expected returns, which have been validated for diversified test portfolios, do not hold with a high level of precision at the individual stock level. This suggests that overexploiting information in factor exposure is not likely to improve

performance. In addition, while there is ample evidence that portfolios sorted on a single characteristic are related to robust patterns in expected returns, such patterns may break down when incorporating many different exposures at the same time.

In the end, the ‘bottom-up’ versus ‘top-down’ debate relates to two factor investing approaches. The first, which supports the ‘bottom-up’ approach, is where the objective of maximising factor exposure justifies renouncing all other dimensions of portfolio construction and notably diversification. The second, which supports the ‘top-down’ approach, considers that the right way to obtain improved risk-adjusted returns associated with factor investing is to reconcile exposure to the rewarded factors with excellent diversification of the non-rewarded specific risks.

In recent research by ERI Scientific Beta (see Amenc et al [2017]) the authors deepen the debate and show that factor concentration alone does not enable solutions to be obtained that have reasonable levels of extreme relative risk and correspond ultimately to solutions with a strong level of turnover, which at an equivalent level of factor intensity (and therefore of variation in relation to the cap-weighted benchmark) have risk-adjusted performances that are lower than factor investing approaches, even naively diversified (equal-weight deconcentration).

In order to reconcile the benefits of strong factor intensity, notably by taking into account the risks of dilution of the factor exposures linked to the negative interactions between factor indices, with those of diversification, ERI Scientific Beta is proposing an evolution of its smart factor indices offering through the application of a high factor exposure filter. This development is in coherence with the Smart Factor 2.0 approach advocated by EDHEC-Risk Institute since 2012.

Reconciling diversification and factor exposure objectives in a top-down framework

Smart factor indices

The smart beta 2.0 index construction approach (Amenc and Goltz [2013]) distinguishes two steps in the construction of smart beta strategies, where the first step tilts towards the targeted risks by way of transparent security selection, and the second step diversifies away the undesired and unrewarded risks by applying a diversification weighting scheme. Amenc et al (2014) use this approach to construct individual smart factor indices tilting towards documented factors, and to assemble ‘top-down’ multi-factor portfolios. A basic smart factor

index is constructed by making a (broad) stock selection on the basis of a single and consensual metric related to the targeted factor (such as the book-to-market ratio for value versus growth selections) and then applying a deconcentration or diversification weighting scheme to the selection. The approach reconciles factor investing with diversification and deals with each in separate steps. Once smart factor indices for different targeted factors have been put together, it is straightforward to implement any multi-factor allocation by blending these indices.

The modularity of the approach allows for dynamic multi-factor allocation through transparent adjustments of single smart factor index weights within the portfolio; this can be used to incorporate tactical views and more importantly for risk management, including the control of risk factor exposures. Transparency and tractability of multi-factor allocations also facilitate risk and performance analysis and reporting. It should be noted that objectives in terms of factor exposure, such as increasing intensity, can also be addressed through allocation decisions across factor indices. A key benefit of the latter approach, which we test in this article, is that it employs well-diversified sub-portfolios to increase factor exposure rather than 'bottom-up' concentration on the basis of noisy stock-level information.

A method to address interaction across factors in a 'top-down' index construction framework

Whatever the methodologies used, the 'bottom-up' approach is based on the idea of selecting factor champions, ie, stocks with the highest multi-factor scores.

However, in a long-only context, it may be less important to identify factor champions than to avoid factor losers as the market tends to penalise the losers more than it rewards the winners. Figure 1 provides an overview of the properties of factor champion portfolios versus factor loser portfolios. The results in the table suggest that the absolute value of under-performance for the factor loser portfolios is greater than the outperformance of the factor champion portfolios. Moreover, it appears that the positive factor intensity of factor champions is of lesser magnitude than the negative factor intensity of factor losers, suggesting that removing losers has a more pronounced impact on overall factor intensity. It should also be noted that the poor factor exposure of factor losers is much more stable than the high factor exposure of factor champion stocks, as evidenced by the lower factor intensity drift of the factor loser portfolios.

In order to integrate these insights into index construction, we test an elimination of stocks with the lowest multi-factor scores within each of six single-factor stock selections prior to applying the diversification weighting schemes. The objective is to obtain smart factor indices with higher factor exposures in multi-factor combinations and we thus term these filtered indices "diversified high factor exposure smart factor indices".

The multi-factor metric chosen is the arithmetic average of the normalised rank scores for five of the six targeted factors (valuation, momentum, volatility, investment and profitability); the size factor is omitted as any diversification weighting scheme induces a tilt away from the largest capitalisations that is not diluted by blending smart factor indices targeting different factors.

Diversified high factor exposure smart factor indices, in addition to achieving the desired factor tilt by way of the initial selection, will

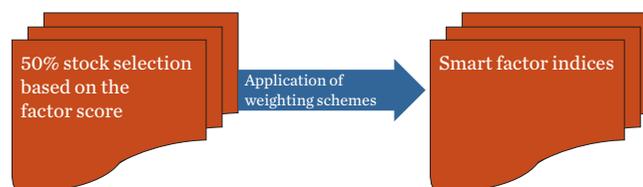
1. Factor champions vs factor losers comparison

US long term 31 Dec 1975–31 Dec 2015	Based on geometric mean		Based on arithmetic mean	
	Champions	Losers	Champions	Losers
5% stock selection				
Annualised relative return	4.42%	-8.96%	3.42%	-6.93%
Sharpe ratio	0.75	ns	0.68	ns
Factor intensity	1.09	-1.97	1.01	-1.56
Factor intensity drift	38.13%	29.85%	48.99%	34.20%
10% stock selection				
Annualised relative return	4.22%	-4.70%	4.55%	-4.89%
Sharpe ratio	0.75	0.06	0.78	0.05
Factor intensity	1.06	-1.23	1.00	-1.25
Factor intensity drift	34.05%	32.04%	34.19%	29.84%

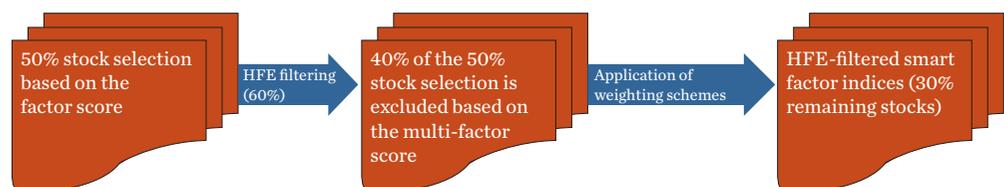
Based on daily total returns in US dollars from 31 December 1975 to 31 December 2015. The EDHEC Risk US LTR cap-weighted index is used as the benchmark. The three-month US Treasury bill rate is used as the proxy for the risk free rate. Champion (loser) portfolios are cap-weighted portfolios of the top (bottom) 5% and 10% stocks selected based on a multi-factor score that is either the geometric mean of the six individual factor scores or the arithmetic mean of the six individual factor scores. The individual factor scores of each stock are the normalised rank scores of the stocks towards the corresponding factor variable. Factor intensity drift is the standard deviation of factor intensity coefficients and is reported in relative terms – ie, is divided by factor intensity of a strategy. In case factor intensity is negative, we use absolute value as a denominator. Factor intensity drift is computed using three-year rolling windows with one-week step size.

2. Construction methodology of smart factor indices with and without the high factor exposure filter

Standard indices



HFE-filtered indices



thus also have aggregate exposure to the other rewarded factors that will be higher than that of their unfiltered counterparts. This will mitigate dilution when indices targeting different factors are blended.

Figure 2 presents the construction methodology of smart factor indices using the high factor exposure filter, compared to the methodology of the standard (unfiltered) version.

We now turn to comparing the score-weighted 'bottom-up' approaches to 'top-down' multi-factor portfolios formed by assembling unfiltered and diversified high factor exposure smart factor indices, respectively.

Comparing 'bottom-up' and 'top-down' approaches

In these comparisons, we benchmark different 'top-down' multi-factor strategies against the concentrated 'bottom-up' approaches – ie, the score-weighted approaches applied to quintile selections. These bottom-up approaches correspond to portfolios formed with 20% stock selection based on a stock-level multi-factor composite score that is either an arithmetic average or a geometric average of the normalised ranks scores of each individual factor. The smart factor indices used as building blocks in the 'top-down' strategies are based on broad selections (half universe) as in Amenc et al

(2014). For the diversified high factor exposure indices, selections are shrunk to 30% of the total number of stocks in the universe. Three 'top-down' portfolios are evaluated, the unfiltered multi-beta multi-strategy six-factor index (equal-weighted), its high factor exposure counterpart, and a solution approach that dynamically allocates to individual diversified high factor exposure smart factor indices to maximise the portfolio's geometric average exposure to the targeted factors – the multi-beta multi-strategy diversified max factor exposure index. The data on these indices are sourced from the ERI Scientific Beta website, where detailed methodologies can also be found. In the context of the 'top-down' portfolios reviewed here, factor exposures are thus used primarily to select broad groups of stocks and, in the context of the diversified max factor exposure index, to make allocation decisions across broad groups of stocks.

Long-term performance and risk measures reported in figure 3 show that all strategies deliver pronounced excess returns and improved Sharpe ratios over the cap-weighted index. They also reveal that the 'top-down' strategies implemented with the diversified high factor exposure smart factor indices cancel half of the performance differential between the unfiltered 'top-down' strategy and the

3. Performance and risk measures

US long term 31 Dec 1975–31 Dec 2015	MFS 20% stock selection Score times cap-weighted based on:			SciBeta 'top-down'		
	Cap-weighted	Arithmetic average	Geometric average	Multi-beta multi-strategy 6F (EW)		
				Standard	Diversified high factor exposure	Multi-beta multi-strategy Diversified max factor exposure
Annualised returns	11.12%	15.75%	15.28%	13.98%	14.79%	14.89%
Volatility	17.04%	13.95%	13.91%	15.18%	13.91%	13.88%
Sharpe ratio	0.36	0.77	0.74	0.59	0.71	0.72
Maximum drawdown	54.31%	45.48%	45.07%	52.59%	48.69%	48.27%
Relative return	–	4.63%	4.16%	2.86%	3.67%	3.77%
Tracking error	–	8.73%	8.45%	4.39%	5.80%	6.39%
Information ratio	–	0.53	0.49	0.65	0.63	0.59
Outperformance probability (3Y)	–	84.32%	79.61%	79.09%	81.26%	79.81%
Extreme relative returns (5%)	–	–13.30%	–13.58%	–6.92%	–8.37%	–9.26%
Extreme tracking error (95%ile)	–	18.06%	16.79%	8.33%	10.87%	12.66%
Maximum relative drawdown	–	51.66%	55.66%	30.34%	36.63%	41.60%
Maximum relative loss	–	0.00%	0.00%	0.03%	0.07%	0.00%

Analysis is based on daily total returns in US dollars from 31 December 1975 to 31 December 2015. Results of three different Scientific Beta 'top-down' approaches are shown as well. EDHEC-Risk USA Long-Term Track Record (LTTR) is used as the cap-weighted benchmark. The risk-free rate is the return of the three-month US Treasury bill. 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. A rolling window of length three years and a step size of one week are used.

◀ narrow-selection score-weighted indices chosen for this acid test. On a total-risk adjusted basis, the multi-beta multi-strategy diversified high factor exposure index and diversified max exposure are arguably in the same class as the score-weighted approaches; however 'top-down' approaches have higher relative-risk adjusted performance. The concentration of the 'bottom-up' approaches contributes to high tracking error resulting in lower information ratios (0.51 on average) compared to 'top-down' approaches (0.62 on average).

Tracking error is also found to increase with concentration for 'top-down' approaches as the diversified multi-beta multi-strategy index boasts the lowest tracking error (4.39%) and the highest information ratio (0.65). The 'top-down' approach that allows for the highest concentration to maximise the composite factor score at the portfolio level exhibits the highest tracking error and the lowest information ratio of the 'top-down' approaches. The diversified max factor exposure index still compares positively to the 'bottom-up' approaches in this regard, illustrating that it retains the diversification benefits which the score-weighted approaches fail to exploit.

Differences are more pronounced when we look at the extreme relative returns and extreme tracking error. 'Top-down' approaches have

significantly lower extreme tracking error than 'bottom-up' approaches (10.62% versus 17.43% on average, ie, an improvement of almost 40%). Similarly 'top-down' approaches have less punishing extreme relative returns (–8.18% versus –13.44% on average, an improvement approaching 40%). Hence the superior long-term performance documented for the narrow-selection score-weighted approaches comes with significant short-term risks.

The results in figure 4 highlight some of the concentration and investability issues of the 'bottom-up' approaches. Since stock-level factor scores change over time, weighting schemes that rely on stock-level scores lead to high turnover compared to strategies that do not overemphasise these stock-level characteristics. The more concentrated the portfolio, the higher the impact of score instability on turnover. The effective numbers of stocks of the 'bottom-up' approaches are consistent with the application of concentrating weighting schemes to a narrow selection and the high levels of turnover observed are then unsurprising as the individual and composite scores have limited persistence. Unsurprisingly, the 'top-down' portfolios have effective numbers of constituents which are consistent with the use of broad stock selections and diversifying weighting schemes at the building block level and the blending of

multiple factor sleeves. The same contribute to their lower turnovers. In the case of the indices implementing equal allocation to the six factor sleeves, the cancellation of cross-trades across sleeves more than offsets the turnover required to periodically reset the allocation. The average difference between the turnover of the flagship multi-beta multi-strategy diversified high factor exposure index and the two bottom-up strategies is 43.35%.

While the volatility of the 'bottom-up' portfolios is close to 20% lower than that of the capitalisation-weighting index of the universe, their GLRs are comparable, which suggests that the lower volatility of these multi-factor approaches is not achieved through better diversification of idiosyncratic risk but instead primarily through concentration in securities that offer lower total volatility (which heightens conditionality risk). The high level of the GLR measure is not surprising since the potential for diversification of a selection of securities is inversely related to their correlations – and it is reasonable to expect that factor champions should show higher correlations to one another than average securities – especially since score-weighted methods make no attempt at exploiting this potential. The GLR measures of the 'top-down' portfolios are significantly better than those of the 'bottom-

4. Investability and diversification measures

US long term 31 Dec 1975–31 Dec 2015	MFS 20% stock selection Score times cap-weighted based on:			SciBeta 'top-down'		
	Cap-weighted	Arithmetic average	Geometric average	Multi-beta multi-strategy 6F (EW)		
				Standard	Diversified high factor exposure	Multi-beta multi-strategy 6F Diversified max factor exposure
Annualised one-way turnover	2.42%	87.39%	67.66%	29.96%	34.18%	56.98%
Capacity	52.28	17.79	7.37	12.91	13.21	12.62
Effective number of stocks	122	34	54	333	195	153
GLR measure	25.76%	25.68%	25.12%	19.41%	20.21%	20.64%
Idiosyncratic risk	–	5.64%	5.21%	3.01%	3.31%	3.57%
Residual Sharpe ratio	–	0.38	0.28	0.46	0.58	0.49
Volatility reduction compared to multi-factor benchmark	–	–2.11%	–1.22%	–2.62%	–3.24%	–2.73%

Analysis is based on daily total returns in US dollars from 31 December 1975 to 31 December 2015. Results of three different Scientific Beta 'top-down' approaches are shown as well. EDHEC-Risk USA LTTR is used as the cap-weighted benchmark. Capacity is the weighted average market capitalisation in \$bn. Volatility reduction is measured as the difference between the volatility of the strategy and its multi-factor benchmark, which is a synthetic portfolio, levered to match returns of the respective strategy, and contains an exactly similar magnitude of systematic risk. The GLR measure is the ratio of the variance of a portfolio's returns to the weighted average of the variance of its constituents' returns. The idiosyncratic risk is based on a seven-factor regression (market + six factors – size, value, momentum, volatility, investment and profitability). The regressions are based on weekly total returns. The market factor is the excess return series of the cap-weighted index over the risk-free rate. Other factors are constructed from the return series of long/short portfolios formed by equally weighting stocks in the top/bottom three deciles of ranks for each factor criterion.

5. Factor exposures

US long term 31 Dec 1975–31 Dec 2015	MFS 20% stock selection Score times cap-weighted based on:			SciBeta 'top-down'		
	Cap-weighted	Arithmetic average	Geometric average	Multi-beta multi-strategy 6F (EW)		Multi-beta multi-strategy 6F Diversified max factor exposure
				Standard	Diversified high factor exposure	
Unexplained	0.00%	2.17%	1.47%	1.38%	1.92%	1.77%
Market	1.00	0.95	0.98	1.00	0.97	0.97
SMB	0.00	0.15	0.19	0.19	0.18	0.18
HML	0.00	0.27	0.31	0.12	0.14	0.18
MOM	0.00	0.10	0.10	0.04	0.04	0.06
LVOL	0.00	0.20	0.18	0.06	0.14	0.12
INV	0.00	0.13	0.13	0.05	0.07	0.13
PROF	0.00	0.15	0.16	0.05	0.09	0.08
R-square	100.00%	83.06%	86.15%	95.98%	94.29%	93.33%
Factor intensity	0.00	1.01	1.08	0.51	0.66	0.75
Excess return/factor intensity	–	4.58%	3.86%	5.61%	5.56%	5.03%
Sharpe ratio of a levered portfolio	–	0.80	0.74	0.83	0.93	0.87
Factor intensity drift	–	0.30	0.42	0.20	0.19	0.23

Based on weekly total returns in US dollars from 31 December 1975 to 31 December 2015. The EDHEC Risk US LTTR cap-weighted index is used as the benchmark. The three-month US Treasury bill rate is used as the proxy for the risk free rate. Market factor is excess returns of cap-weighted index over the risk-free rate. Other factors are constructed from the return series of long/short portfolios formed by equal weighting stocks in the top/bottom three deciles of ranks for each factor criterion. Factor intensity is the sum of all betas except for market beta. Excess returns over factor intensity is a measure of relative return to the cap-weighted index per unit of factor intensity. Sharpe ratio of a levered portfolio is based on the returns of a portfolio that was levered up with the objective of achieving the same factor intensity as the one with the maximum factor intensity among the strategies reported in the table, which equals 1.08. Factor intensity drift is the standard deviation of factor intensity coefficients and is reported in relative terms – ie, is divided by factor intensity of a strategy. Factor intensity drift is computed using three-year rolling windows with one week step size. Coefficients with p-value lower than 5% are reported in bold.

up' portfolios, whereas their total volatilities are similar or higher, which suggests better diversification of idiosyncratic risk. The lower levels of standard deviations of residuals and the superior residual Sharpe ratios displayed by the 'top-down' approaches are also consistent with high diversification. These improvements in diversification can be expected to lead to improved risk-adjusted performance at a given level of factor intensity. Indeed, such improved diversification should provide efficient harvesting of factor premia, whereas a sole focus on increasing intensity without diversifying unrewarded risks is likely to prove inefficient.

The figures in figure 5 on long-term factor exposures confirm that the use of diversified high factor exposure smart factor indices delivers 'top-down' multi-factor portfolios that display significantly increased factor exposures; unsurprisingly, the diversified max factor exposure index achieves the highest factor intensity with an increase of close to 50% relative to the unfiltered multi-beta multi-strategy index. Just as unsurprisingly, the 'bottom-up' strategies produce the highest exposures.

However, 'top-down' approaches deliver higher excess returns per unit of factor intensity – on average circa 25% more than 'bottom-up' strategies. The Sharpe ratios of portfolios that have been levered to achieve the highest factor intensity delivered by the 'bottom-up' approaches are consistently higher

for 'top-down' strategies. These results clearly suggest that relative to multi-factor 'top-down' approaches, score-weighted strategies deliver their higher factor intensities in an inefficient way.

Figure 5 also assesses the instability of factor exposures. It is worth pointing out that the 'bottom-up' approach that produces the highest factor intensity also suffers the highest absolute and relative instability of this intensity. The intensity drift of the 'bottom-up' approaches is twice as high as for the 'top-down' approaches built with diversified high factor exposure indices. The 'top-down' approaches deliver higher excess returns per unit of factor intensity (5.40% on average) compared to that of 'bottom-up' portfolios (4.22%). This represents a 28% increase in excess returns per unit of factor intensity.

Conclusion

It appears that by ignoring the central tenet of modern portfolio theory to focus solely on increasing factor score intensity and by assuming strong relationships between security-level scores and performance, score-weighted approaches expose investors to risks that are unrelated to factors and for which no reward should be expected. We find that focusing solely on increasing factor intensity leads to inefficiency in capturing factor premia, as exposure to unrewarded risks more than offsets the

benefits of increased factor scores. High factor scores in 'bottom-up' approaches also come with high instability and high turnover. We introduce an approach that considers cross-factor interactions in 'top-down' portfolios through an adjustment at the stock selection level. This approach, while producing lower factor intensity than 'bottom-up' methods, leads to higher levels of diversification and produces higher returns per unit of factor intensity. We find that it dominates 'bottom-up' approaches in terms of relative performance, while considerably reducing extreme relative losses and turnover.

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Measuring and managing systematic and specific risk of smart beta benchmarks

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seminar

Towards better infrastructure investment products?

Frédéric Blanc-Brude, Director, EDHECinfra; Grace Chen, Senior Relationship Manager, EDHECinfra; Tim Whittaker, Associate Research Director, EDHECinfra

In a new paper sponsored by the Global Infrastructure Hub (a G20 Initiative), EDHECinfra presents the results of the first in-depth survey of institutional investors' perceptions and expectations of infrastructure investment.

It documents the reasons for investing in infrastructure and whether currently available investment products or strategies are helping investors meet these objectives. The findings provide a first step towards integrating infrastructure in long-term investment solutions.

The survey reports the views of 184 individuals involved in infrastructure investment; half of them represent institutional investors or 'asset owners' (insurers, pension plans and sovereign wealth funds), one-third are infrastructure asset managers and the remainder are infrastructure investment specialists from multilateral development banks, rating agencies and consultancies. Respondents are mostly senior executives active in the top management (CEO, board members – 14.5%), strategic (CIO, head of ALM or asset mix – 25.5%), investment (head of infrastructure, investment director – 46.2%) or other (14.5%) functions of the organisations they represent.

Infrastructure is popular. Almost two-thirds of surveyed institutions declared that they wanted to increase their current holdings of infrastructure investments. Beyond that unsurprising point, the survey reveals some important evolutions and also important differences of perspectives, among investors and also between asset owners and managers.

In what follows, we summarise the findings of the survey and provide some elements for discussion and future research.

Investment beliefs

Key findings

The main findings on asset owners' and managers' investment beliefs are:

- There is wide disagreement among respondents about whether listed infrastructure equity or debt qualify as an asset class. However, unlisted infrastructure is widely considered to be a 'unique' asset class, both on the private debt and privately-held equity sides;
- Most respondents also believe that focusing on infrastructure investment only makes sense if it can be defined as an asset class, whereas a minority reports preferring to approach infrastructure as an investable bundle of factor exposures;
- Most respondents perceive infrastructure investment's unique feature to be either its potential for portfolio diversification or for harvesting risk premia, whereas it is less frequently believed that infrastructure has unique interest rate or inflation-hedging properties;
- Investors and managers define infrastructure in terms of long-term contractual arrangements and monopoly regulation and acknowledge that

- We present the results of the first in-depth survey of institutional investors' perceptions and expectations of infrastructure investment.
- It documents the reasons for investing in infrastructure and whether currently available investment products or strategies are helping investors meet these objectives. The findings provide a first step towards integrating infrastructure in long-term investment solutions.
- The survey reports the views of 184 individuals involved in infrastructure investment; half of them represent institutional investors or 'asset owners' (insurers, pension plans and sovereign wealth funds), one-third are infrastructure asset managers and the remainder are infrastructure investment specialists from multilateral development banks, rating agencies and consultancies.
- Key findings are reported in the following areas: investment beliefs; products and objectives; benchmarking; and ESG (environmental, social and governance).

industrial sectors are a much less informative way to categorise such investments. In the same spirit, the stability of long-term contracts and the role of counterparty risk are perceived to be the most important and unique characteristics of infrastructure firms (compared to other firms). Finally, 'brownfield' (existing) and 'contracted' infrastructure is reported to be the most attractive to investors, closely followed by brownfield regulated utilities;

- Expected returns follow a clear pattern determined by the 'business model' (contracted, merchant or regulated) and the lifecycle (greenfield or brownfield) of infrastructure firms, with greenfield merchant investments requiring higher returns than brownfield regulated and contracted infrastructure;
- Despite viewing infrastructure as characterised by stable long-term contracts and being most attractive once it has been built, most investors and their managers expect relatively high returns. A majority considers that infrastructure assets should not be 'expensive' and requires equity returns ranging from the high single digits to the low teens. Asset managers systematically report higher expected returns than asset owners.
- More than half of participating asset owners declare that they are investing in emerging markets or wish to, and that they are willing to increase their current allocation. SWFs and pensions plans are the most involved and willing types of investors investing or aiming to invest in emerging market infrastructure;
- The main reported reasons for expanding into emerging market infrastructure are higher returns and country risk diversification, while the main concerns of investors are public policy

reversals and the enforceability of contractual claims.

- Required returns in emerging markets are higher but otherwise follow the same patterns as in OECD markets. However, the emerging market premium on returns varies for different types of infrastructure projects: investments in the contracted and regulated categories command much higher spreads (above the OECD required returns), particularly at the brownfield stage, whereas emerging market merchant risk is perceived to be almost equivalent to OECD merchant risk.

From homogenous to heterogeneous beliefs

These results highlight the degree to which investors agree or disagree about what to expect from investing in infrastructure equity or debt.

Infrastructure has long been considered difficult to define as an investment proposition but a consensus view is emerging among market participants about the nature of infrastructure business, and what drives risk and performance in such investments. Hence, what qualifies or not as infrastructure is now better understood, as the recent debate around the definition of infrastructure investment in the context of the Solvency-II directive has shown.

As a result, investors express views about expected returns which are coherent with the risk matrix proposed in Blanc-Brude, Hasan, and Ismail (2014) and Blanc-Brude and Hasan (2015) for instance, by which systematic risk in infrastructure investment can in part be broken down according to a simple 3×2 matrix made up of three business models (contracted, merchant and regulated) and two key moments in the lifecycle of infrastructure projects (greenfield and brownfield).

A third dimension of the risk profile of infrastructure investments is country or jurisdiction risk, which is confirmed by the reported returns required by investors for emerging market infrastructure. Interestingly however, the 3×2 pattern described above is not changed by the addition of emerging market risk: relatively speaking, greenfield risk is still attracting higher returns than brownfield and contracted infrastructure but less than projects exposed to merchant risk.

However, the premium reported for taking emerging market risk is driven by considerations that are specific to these jurisdictions: the lower end of the risk spectrum in OECD infrastructure (brownfield contracted and regulated infrastructure) is what attracts the highest relative premium in emerging markets.

This validates the focus on contracts as the determinants of the risk profile of infrastructure investments: the higher risks found in emerging markets spring from – respondents report – the quality of the contracting framework and the ability to enforce contractual claims. ▶

◀ Hence, the more infrastructure investments rely on contracts (when it belongs to the ‘contracted’ business model and in the long-term – ie, at the brownfield stage) the more they attract relatively higher risk premia in emerging markets.

While the asset pricing implications make sense, these results are also striking from a public policy perspective: countries that have a bad track record at respecting and enforcing contractual claims pay a significant premium on their privately-financed infrastructure – one that, in all likelihood, renders uneconomic many potential private investment projects in these jurisdictions. Beyond the homogeneity of investors’ beliefs in terms of the risk and returns components of infrastructure investments, survey results also highlight the heterogeneity of views around these fundamental building blocks. Different types of asset owners tend to report different preferences and views are also highly heterogeneous between individual investors of the same type.

That investors require a range of returns for comparable risk profiles (ie, within one family of infrastructure investments) is congruent with the notion that in incomplete markets, the law of one price does not apply and large bid/ask spreads remain. In this survey, the reported range of expected returns is considerable, with similar risk profiles attracting return requirements ranging from less than 5% to more than 15%.

Finally, the fact that asset managers systematically report higher expected returns than asset owners can also be interpreted as a reflection of the agency issues found between investors (limited partners – LPs) and general partners (GPs) which we discuss at length below.

Products and objectives

Key findings

With respect to available investment options and the objectives pursued by asset owners investing in infrastructure, key findings of this survey include:

- ➔ The immense majority of asset owners are rather dissatisfied with existing infrastructure investment products;
- ➔ Fee levels is the first reason for this state of affairs and in second place is the absence of well-defined investment objectives of the various infrastructure funds and platforms;
- ➔ Even co-investment alongside managers or banks is considered by almost half of asset owners to be only a second best option, ie, they would rather have access to the investment products they need and want.
- ➔ The immense majority of asset owners consider the classic closed-ended private equity infrastructure fund model to be ‘outdated’ and ‘not adding value’;
- ➔ The majority of investors also declare that they are either ‘concerned’ or ‘very concerned’ about the accumulation of ‘dry powder’ in numerous infrastructure fund mandates, because it could lead to a deterioration of investment/underwriting standards, if not the creation of ‘Ponzi units’;
- ➔ Most respondents concur in saying that infrastructure investment only really makes sense as a long-term strategy (beyond 10 years), and a majority declares itself willing to buy and hold infrastructure investments until maturity. Logically, but perhaps surprisingly, most investors report not being particularly concerned by the absence of liquidity of such investments;
- ➔ Most investors declare that they prefer to invest in privately-held infrastructure debt or equity – as opposed to public stocks or bonds –

but they are evenly divided between those who prefer direct investment and those who would rather delegate to a manager.

➔ Overall, the objectives pursued through infrastructure by the majority of investors are linked to improving diversification and achieving higher performance. Other objectives that are intuitively associated with infrastructure investing such as hedging inflation or interest risk are less present in the series of objectives currently being pursued. However they are among the highest-ranked objectives that investors would like to be able to achieve through infrastructure investing (along with stable cash flows and illiquidity premia).

Market failure?

Combined with the most recent reports on infrastructure fund raising – which is at historic heights – these results reveal something like a quandary: at least half of investors would like to invest through a manager but the immense majority of them complain that existing products are too expensive and not designed to help them achieve their goals. As we report in the next section, more than half of them do not even trust the performance metrics reported by infrastructure asset managers.

The market to provide access to infrastructure investment through investment funds is large and growing, and the number of asset managers active in this space is also significant. It can be surprising that competition between GPs for the attention of LPs does not lead to a more aggressive levelling of fees or the design of different types of infrastructure funds. In effect, a small number of asset managers do offer longer, less aggressive and less expensive infrastructure funds than the mainstream infrastructure PE funds, but they represent a minority of the total fundraising.

Why do asset owners continue to invest in infrastructure funds that 80% of them consider to be ‘outdated and not adding value’?

When institutions allowing market participants to trade without restriction on prices or volumes are in place and the expected benefits of competition fail to materialise, the market mechanism can be considered to be failing. In effect, it can be argued that the market for delegated investment management in the infrastructure sector is at least partly failing to create the kind of products that investors need, let alone at a fair price.

Next, we discuss why a market can be stuck in a suboptimal equilibrium, in which investors only have access to inadequate and expensive products.

Say a market for investment management services is characterised by different types of service providers (in this case, infrastructure asset managers): these managers can be more or less capable – that is, more or less able to select and manage infrastructure debt and equity investments to build a portfolio that has certain characteristics of interest to asset owners.

The different types of managers can also be distributed more or less evenly: for instance there could be a few capable managers and many less capable ones.

Asset owners who need to choose an infrastructure asset manager are then faced with a simple problem: they do not know which ones are the capable ones and which ones are not. They are said to be facing the problem of adverse selection.

Next, say that asset managers also have the

option of making a certain effort to create the kind of infrastructure investment product that investors would prefer. This effort is costly to the manager but it leads to the creation of better products, eg, better-defined duration and risk factor exposures. Hence, investors are also faced with a case of moral hazard: they need to create incentives to induce asset managers to exert a costly effort to deliver the kind of products that best utilise the characteristics of infrastructure assets to achieve their investment objectives.

If the capable managers do make this effort and propose better investment products, investors can choose the products they need and maximise their long-term utility. If the less capable asset managers made the same costly effort, they would go out of business and be forced to exit the market.

With perfect information about manager type and what investment products can be created by investing in infrastructure, competition would work as expected: investors would require the products that are best suited to their needs and the capable managers would provide them, and competition in the market would be limited to the capable types.

The difficulty arises from the absence of information (eg, benchmarking) for asset owners, who do not know exactly what infrastructure investing can do for them and cannot easily discriminate between different types of managers.

Without perfect information however (the asset owners will have no knowledge of the managers’ type), capable managers can simply mimic the less capable ones, make no costly effort to design better investment products and provide the same ‘outdated’ products like any other providers. What drives up costs in this case is not the absence of competition, but the tendency for all managers to ‘pool together’ and behave like the least capable ones.

The presence of asymmetric information between buyers and sellers affects the functioning of markets and can lead to market failure: either the absence of trade (investors exit the market and decide to internalise infrastructure investment – ie, the so-called Canadian model) or a very suboptimal trade characterised by the pooling of manager types (all managers provide the same products). In the latter case, asset owners buy investment products that are not what they need and at a high price given the utility they derive from them, and even the more capable managers tend to offer standardised, relatively inadequate products, while they could achieve a greater market share by offering advanced investment solutions.

Next, we discuss both cases in more detail.

The costs of rejecting delegation

Faced with the kind of market failure described above, a first group of participants chooses to exit and address agency issues under asymmetric information by internalising the investment function, in this case by building up internal capability to source and execute infrastructure transactions, manage infrastructure firms throughout their lifecycle and receive the benefits of direct control, asset selection and transaction timing, including – as the majority of survey respondents declared – the option to hold investments to maturity.

Borrowing from the vocabulary of behavioural studies in the retail pension sector, these do-it-yourself investors also tend to be the most ‘engaged’ and sophisticated ones, whereas others, probably smaller investors, for whom infrastructure may be a much newer theme, can be described as ‘passive’.¹

For engaged investors to be better off fol-

1 Still, it is also possible for large direct investors in infrastructure to retreat from the DIY approach and to return to managed infrastructure mandates. The Victoria Fund Management Corporation is one such recent example.

lowing the DIY approach than delegating to a specialist manager, they must be able to deliver results which are at least as good as those products provided by the best managers in the market (net of costs).

The net benefits from choosing direct investment are thus determined by three factors:

➔ **Investment costs:** with limited effects of competition between managers on fees, some asset owners have come to the conclusion that internalising infrastructure investment can be worthwhile. Nevertheless, a fully-fledged infrastructure team is only available to large investors. Such teams may also encounter their 'lifecycle' issues as investors buy infrastructure firms (transaction structuring and execution) and operate them on a buy-to-hold basis (asset² management), the required skill-set must change over time. It is also possible that some agency issues that exist between asset owners and managers are simply re-created internally between the strategic asset allocation level and the investment level.

➔ **Diversification benefits:** building a direct portfolio of infrastructure assets is a long-term goal in itself. The recent experience of some Australian or Canadian investors suggests that it can take at least 10 to 15 years. Even so, the resulting portfolio of 20 to 25 investments is unlikely to be well diversified and may even include very concentrated exposures (ie, a few very large firms). Of course, the main diversification benefits of infrastructure investment accrue to the portfolio as a whole, as survey responses suggest, but less diversification of the infrastructure portfolio itself can be considered a straight loss. In principle, investors should be able to diversify better by investing across a range of infrastructure funds, themselves exposed to a range of infrastructure business models, lifecycle stages and jurisdictions. The extent of the failure of the market for delegated investment in infrastructure is highlighted by this fact: a growing number of large investors prefer forgoing diversification benefits in favour of a more concentrated, internally-managed portfolio.

➔ **Portfolio construction:** Against these costs (fees and lower diversification) investors expect benefits that are themselves dependent on what portfolio of infrastructure assets each one of them can build. Different investors have different objectives and liability profiles which cannot be answered *ex ante*. Full control over the investment process may allow asset owners to build infrastructure portfolios that are more in line with their objectives. However, if a well-functioning market for investment delegation led to the creation of better-defined investment products using infrastructure debt and equity to target a given set of financial metrics, the potential contribution of such products may outweigh the benefits of control on asset selection and infrastructure portfolio construction.

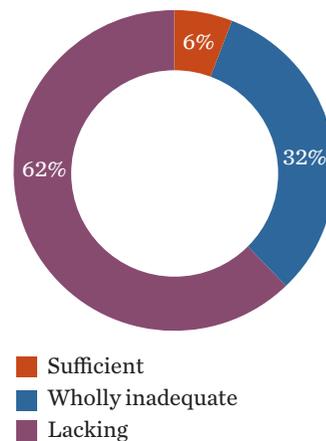
Thus, the net benefits of internalising long-term investment in infrastructure are not self-evident once the possibility to improve investment products is taken into account.

These issues hinge around the absence of sufficient information about what can be achieved through infrastructure investment and who can commit to achieving such goals.

Market solutions: benchmarking and signalling

Why are the more capable infrastructure asset managers not offering different products to the classic two-and-twenty, closed ended PE fund? In the classic adverse selection model, the more capable type of manager is simply better off in the short term mimicking the less capable type,

1. Current options to benchmark private investments in infrastructure are:



and making no costly effort to deliver a better service.

But it can also be the case that the most competent managers would be better off providing more advanced products (they would gain market share) but cannot effectively articulate and demonstrate the added-value they could create by designing different forms of infrastructure investment products.

If information asymmetry is too strong then what might be achievable through new forms of infrastructure investment products may be very challenging to communicate effectively to asset owners, who remain faced with the Scylla of DIY investing and the Charybdis of infrastructure PE funds.

There are however solutions to minimise the effect of information asymmetry in market dynamics. To avoid the pooling of managers, market participants can create 'sorting devices' (Spence [1973]; Rothschild and Stiglitz [1992]) or 'revelation mechanisms' (Laffont and Martimort [2002]) to facilitate the processing of information from uninformed to informed participants.³

The more capable asset managers may also try to signal their ability to create better products to asset owners through various devices (eg, certification schemes).

In economics, this problem is typically modelled as a market with adverse selection and competitive search, where some agents post terms of trade (contractual terms) and others aim to screen the other side of the trade by agent type (see for example, Guerrieri, Shimer, and Wright [2010]). In such models, the informed side of the trade (here the asset manager) can move first and signal to the market what terms they can offer, or the uninformed side can move first and request a bid for a given 'menu of contracts'.

In other words, either asset owners could request bids in an auction for a limited number of well-defined investment products, or asset managers could choose to highlight the different products that are available through the kind of performance reporting standard, valuation approaches and performance benchmarks that we discuss next.

Benchmarking

Key findings

On the topic of benchmarking the performance of infrastructure investments, the main findings of the survey are:

- ➔ Investors' current use of benchmarks for their infrastructure investments is as likely to be relative or absolute, nominal or real, or relative to a market or a macroeconomic index. There is no clear market practice;
- ➔ In fact, the immense majority of investors and managers agree that currently available benchmarks are inadequate and that proper infrastructure investment benchmarks just do not exist (figure 1);
- ➔ Survey respondents confirm that risk metrics in particular are not documented and that valuations are sufficiently problematic to cast doubt on any measure of returns as well. More than half of asset owners reckon that they either do not trust or do not know if they can trust the valuations reported by the infrastructure asset managers.

Towards better benchmarks

Roadmap and recent progress

In June 2014, Blanc-Brude (2014) put forward a roadmap for the creation of infrastructure investment benchmarks. This roadmap integrates the question of data collection upfront, including the requirement to collect information known to exist in a reasonably standardised format and limited to what is necessary to implement robust asset pricing and risk models. It puts forward the following steps:

- ➔ Defining the relevant instruments;
- ➔ Developing a relevant asset pricing framework;
- ➔ Defining the necessary data;
- ➔ Building a global database of cash flows and investment characteristics;
- ➔ Building reference portfolios of infrastructure equity and debt.

The implementation of this roadmap is described in detail in Blanc-Brude (2014) and recent progress in Blanc-Brude et al (2016).

Defining infrastructure investments from a financial perspective, the only relevant perspective to build investment benchmarks, is a necessary first step. As the results of this survey and the recently proposed definition put forward by the European regulator of pension plans and insurance companies suggest, defining infrastructure investment from an investment perspective has progressed considerably. The growing consensus reflected in this survey around the limited role of industrial sector categories in explaining and predicting performance, and the much more significant role played by contracts and by different infrastructure 'business models' such as 'merchant' or 'contracted' infrastructure, or various forms of utility regulation, is encouraging.

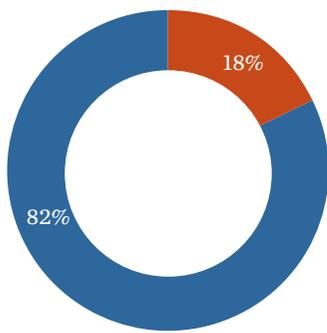
Once the financial instruments that correspond to infrastructure investment are usefully defined, the second necessary step is to design a performance and risk measurement framework that can provide robust answers to the questions identified above. Again, our survey responses confirm the urgent need to improve the current methodologies to evaluate private assets given the increasingly important they play in investors' portfolios.

Privately-held, infrastructure equity and debt instruments are not traded frequently and cannot be expected to be fully 'spanned' by a combination of public securities. Hence, they are unlikely to have unique prices that all investors concur with at one point in time. ▶

² The infrastructure asset.

³ For example, Hellwig (1987) discusses the role of deductibles in insurance contracts and how the choice of deductible can be used by insurers to infer the probability of accident of a given individual.

2. Is the classic closed-ended PE fund with fund-level leverage in addition to asset-level leverage:



- A perfectly justified way to approach infrastructure investment
- Outdated and not adding value

Asset owners only.

◀ A two-step approach to measuring performance is therefore necessary:

- Documenting cash flow distributions (debt service and dividends) to address the fundamental problem of unreliable or insufficiently reported NAVs or losses given default (LGDs);
- Estimating the relevant (term structure of) discount rates, and relevant rates of returns, and their evolution in time.

Here too, progress has been made and recent research provides a framework addressing both steps, taking into account the availability of data, while applying best-in-class models of financial performance measurement (see for example Blanc-Brude, Hasan and Ismail [2014]; Blanc-Brude and Hasan [2015] for applications to the private debt and equity case).

Based on this new asset pricing and risk measurement technology, a list of data items required to implement adequate methodologies can be drawn up that can be used to collect data and populate the necessary database but also to determine a minimal reporting framework for investors to require from infrastructure managers. These data collection requirements are described in Blanc-Brude et al (2016).

The active collection of the necessary data and publication of the relevant investment benchmarks has begun to be implemented with the creation of the EDHEC Infrastructure Institute in Singapore in February 2016 and is planned to take place incrementally until 2020 and beyond.

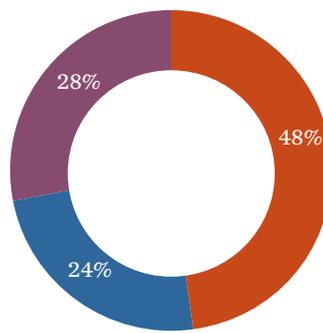
Benchmarking as signalling

In this survey and in others before, asset owners highlight high fees, insufficient performance reporting and inadequate valuation methods as some of the main issues found in delegated private investment.

In recent years, however, asset owners have begun to question the level of investment fees and to achieve substantial reductions in the overall level of investment management fees, through self-organisation as well as with the help of the regulator.

As we argued above, high fees are only the result of the information asymmetry that exists between asset owners and managers. The crux of the matter hinges around reported valuations. The valuation of private assets is the primary source of information asymmetry between managers and asset owners. Hence, with the

3. Do you trust the asset valuations reported by infrastructure managers?



- Yes
- Not sure
- No

Asset owners only.

argument to lower fees gradually being won by LPs, the next big issue to open for review is asset valuation (figure 3).

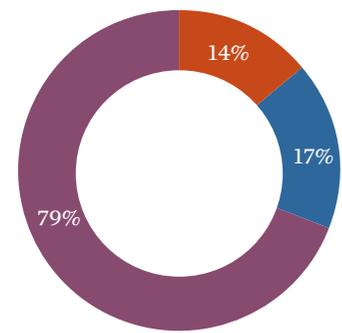
Private asset valuation has long suffered from numerous flaws, in particular the classic stale pricing problem and the corollary smoothing of asset returns (see Blanc-Brude and Hasan [2015] for a review of the literature on the subject applied to infrastructure). As we suggested above, a number of technical improvements are possible that allow better measurements of risk-adjusted performance in private infrastructure investments. In due course, further development in applied academic research will allow for even more robust and advanced methods to be implemented.

The matter of reporting adequate performance data and applying state-of-the-art valuation methodologies is also relevant to the 'sorting mechanisms' or 'signalling' that we discussed above when suggesting solutions to the market failures found in delegated investment management. When information asymmetries are so significant that asset owners cannot know which managers are the capable or the less capable ones, they could require managers to adopt a certain reporting framework and to implement advanced valuation methods to make the more competent managers 'reveal their type'. Likewise, individual managers could offer to adopt an equivalent reporting and valuation framework to make asset owners aware of their type.

Once the more capable managers have agreed to reveal their type or have been identified by asset owners, it becomes possible for the latter to require that they exert the kind of effort that should lead to the creation of better investment products. Note that revealing their types for the better managers is not free and that – in the standard solution to the principal agent problem with adverse selection and moral hazard – the incentive compatible contract between the client and the service provider requires that a premium be paid to the agent of the desirable type. However, the net (after fee) benefits to asset owners should now be much higher (if not, then internalisation – the DIY option – remains the preferred route).

Beyond type revelation or discovery, the last missing element in the relationship between principal and agent is for asset owners to actually know what to ask the better managers to do

4. How principled is institutional investors' stance on the ESG aspects of their infrastructure investments?



- ESG is unimportant in comparison with financial objectives
- ESG is a first-order problem, possibly at the expense of performance
- ESG is somewhat important but not an overriding consideration (a second-order problem)

Asset owners only.

for them through infrastructure investment.

Infrastructure investment benchmarks are at the heart of this issue: with fully-fledged benchmarks, what is achievable for investors through infrastructure investment can be known (eg, what combination of factor exposures infrastructure investment can create) and only then can asset owners request their managers to build infrastructure portfolios for them that are fully integrated into a long-term investment solution for them.

In effect, private infrastructure investment benchmarks can improve most issues of information asymmetry between investors and managers since they can be used both to determine what investors should require and to signal what managers can or cannot deliver.

ESG

Key findings

Regarding the environmental, social and governance impact of infrastructure investment, asset owners' responses suggest that:

- Investors acknowledge the relevance of ESG considerations but a majority considers ESG to be a second-order problem – ie, one that does not trump first-order questions like strategic asset allocation (figure 4);
- Nevertheless, 17% of owners consider ESG to be a first-order question;
- Most respondents also expect ESG to be positively related to investment returns.

Does ESG mean more or less risk?

Institutional investors all have well-defined mandates to, for example, ensure the delivery of pension benefits, the solvency of insurance schemes or the preservation of national wealth. Respecting these different mandates means achieving a series of nominal or real wealth objectives at certain horizons and preserving the funding level (liabilities versus assets) of each institution at each point in time. In other words, it means focusing on risk-adjusted financial performance, which is, in turn, the result of strategic asset allocation decisions.

This is every asset owner's first-order problem.

To the extent that investors also want to avoid investing in certain types of infrastructure projects (eg, coal-fired power plants) or ensure that the social consequences of new projects (eg, hydroelectric dams) are limited and well managed, the considerations must nevertheless remain subordinated to achieving long-term financial objectives.

It does not mean that investors 'do not care' about investing in less sustainable businesses or projects, but simply that they have to meet certain objectives first, and that ESG investing would be self-defeating if it undermined their ability to achieve these goals. In fact, being able to pay the pensions and life insurance policies of millions of individuals is nothing short of a very worthy social goal.

Still, in this survey, 17% of asset owners consider that ESG is nevertheless a first-order problem. Moreover, it is likely that this number has been increasing and that even more investors would give this answer in a future iteration of this survey.

ESG investing can be modelled as a form of 'guilt aversion' – a notion developed in behavioural economics – by which investors could be willing to forgo some level of performance or future income to avoid investing in certain types of assets. In this case, there is a mostly negative trade-off with performance and ensuring a minimal threshold of ESG quality in new investments can also be understood as a form of risk management: new infrastructure projects that are less likely to create environmental or social issues may also be less likely to experience regulatory or policy shocks in the future. If this is the case then higher ESG

criteria should be synonymous with lower expected returns.

Still, the majority of respondents believe that there is a positive link between returns and ESG quality, implying higher risk-taking in such projects. For instance, investing in renewable energy and reducing carbon emissions qualifies as having a positive environmental impact but also rests on publicly-sponsored tariff subsidy schemes that are prone to change over the decades that each wind or solar farm investment is supposed to last. Recent evidence of changes in wind farms' feed-in-tariff, sometimes retroactively, is plentiful in European markets for instance.

Another aspect of ESG in the context of infrastructure investments is job creation. While this can be considered a positive in regards to the social and political acceptance of private infrastructure investment (the so-called 'social licence to operate' of the private sector), committing to employing a certain workforce may create long-term issues regarding operational efficiency given the impact of technological change over several decades. The impact of containerisation in the port sector is a good example of a sector that had to let go most of its workforce over a couple of decades.

If investors expect higher returns from ESG compliant investments, it may be interpreted as an increase in risk aversion vis-à-vis an economic future which changing environmental and social issues make increasingly uncertain or, perhaps more simply, the recent drive towards ESG could be seen as part of a broader increase in investor risk appetite in a low yield environment.

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Looking for a listed infrastructure asset class

Frédéric Blanc-Brude, Director, EDHECinfra; Tim Whittaker, Associate Research Director, EDHECinfra; Simon Wilde, Research Associate, EDHECinfra;

In a new EDHECinfra paper, we ask the question: does focusing on listed infrastructure stocks create diversification benefits previously unavailable to large investors already active in public markets?

This question arises from what we call the "infrastructure investment narrative" (Blanc-Brude 2013), a set of investment beliefs commonly held by investors about the investment characteristics of infrastructure assets.

According to this narrative, the 'infrastructure asset class' is less exposed to the business cycle because of the low price-elasticity of infrastructure services. Furthermore, the value of these investments is expected to be mostly determined by income streams extending far into the future, and should thus be less impacted by current events.

According to this intuition, listed infrastructure may provide diversification benefits to investors since it is expected to exhibit low return covariance with other financial assets. In other words, listed infrastructure is expected to

- ➔ We ask whether focusing on listed infrastructure stocks creates diversification benefits previously unavailable to large investors that are already active in public markets. This would mean that listed infrastructure is expected to exhibit sufficiently unique characteristics to be considered an 'asset class' in its own right.
- ➔ We conclude that in general, what is typically referred to as listed infrastructure, defined by SIC code and industrial sector, is not an asset class or a unique combination of market factors, but instead cannot be persistently distinguished from existing exposures in investors' portfolios, and that expecting the emergence of a new or unique 'infrastructure asset class' by focusing on public equities selected on the basis of industrial sectors is misguided.
- ➔ Asset owners and managers who use the common 'listed infrastructure' proxies to benchmark private infrastructure investments are either misrepresenting (probably over-estimating) the beta of private infrastructure, and usually have to include various 'add-ons' to such approaches, making them completely ad hoc and unscientific.
- ➔ By defining infrastructure according to the relationship-specific and contractual nature of the infrastructure business, we find that listed infrastructure may help identify exposures that have at least the potential to persistently improve portfolio diversification on a total return basis.

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◀ exhibit sufficiently unique characteristics to be considered an ‘asset class’ in its own right.

Empirically, there are at least three reasons why this view requires further examination:

- ➔ Most existing research on infrastructure has used public equity markets to infer findings for the whole infrastructure investment universe, but robust and conclusive evidence is not forthcoming in existing papers;
- ➔ Index providers have created dedicated indices focusing on this theme and a number of active managers propose to invest in ‘listed infrastructure’ arguing that it does indeed constitute a unique asset class;
- ➔ Listed infrastructure stocks are often used by investors to proxy investments in privately held (unlisted) infrastructure equity, but the adequacy of such proxies remains untested.

The existence of a distinctive listed infrastructure effect in investors’ portfolios would support these views. In the negative, if this effect cannot be found, there is little to expect from listed infrastructure equity from an asset allocation (risk/reward optimisation) perspective and maybe even less to learn from public markets about the expected performance of unlisted infrastructure investments.

There is no listed infrastructure asset class

We test the impact of adding 22 different proxies for ‘listed infrastructure’ to the portfolio of a well-diversified investor using mean-variance spanning tests. We focus on three definitions of ‘listed infrastructure’ as an asset selection scheme:

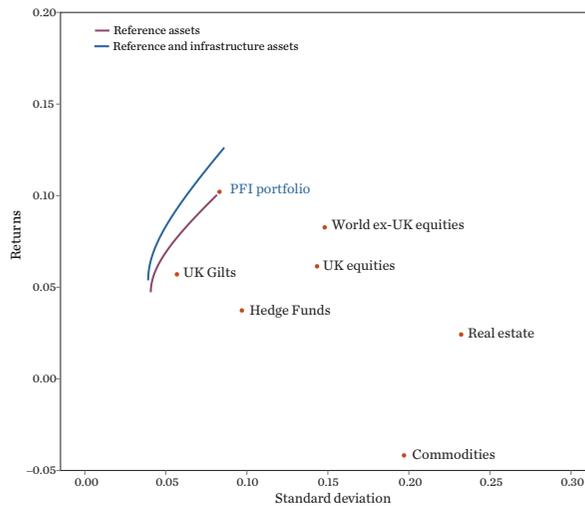
- ➔ A ‘naïve’, rule-based filtering of stocks based on industrial sector classifications and percentage income generated from predefined infrastructure sectors (nine proxies);
- ➔ Existing listed infrastructure indices designed and maintained by index providers (12 proxies);
- ➔ A basket of stocks offering a pure exposure to several hundred underlying projects that correspond to a well-known form of infrastructure investment defined – in contrast with the two previous cases – in terms of long-term public-private contracts, not industrial sectors (one proxy).

Employing the mean-variance spanning tests originally described by Huberman and Kandel (1987) and Kan and Zhou (2012), we test the diversification benefits of these proxies for the listed infrastructure effect.

Some stylised findings include:

- ➔ Our 22 tests of listed infrastructure reveal little to no robust evidence of a ‘listed infrastructure asset class’ that was not already spanned by a combination of capital market instruments and alternatives, or by a factor-based asset allocation;
- ➔ The majority of test portfolios that improve the mean-variance efficient frontier before the global financial crisis (GFC) fail to repeat this feat post-GFC. There is no evidence of persistent diversification benefits;
- ➔ Of the 22 test portfolios used, only four manage to improve on a typical asset allocation defined either by traditional asset classes or by factor exposure after the GFC and only one is not already spanned both pre- and post-GFC;
- ➔ Building baskets of stocks on the basis of their SIC code and sector-derived income fails to generate a convincing exposure to a new asset class.
- ➔ Hence, benchmarking unlisted infrastructure investments with thematic (industry-based) stock indices is unlikely to be very helpful from a pure asset allocation perspective – ie, the latter do not exhibit a risk/return trade-off or betas that large investors did not have access to already.

1. Efficient frontier January 2000–December 2013



Overall, we do not find persistent evidence to support the claims that listed infrastructure is an asset class. In other words, any ‘listed infrastructure’ effect was already spanned by a combination of capital market instruments over the past 15 years in global, US and UK markets.

We show that defining infrastructure investments as a series of industrial sectors and/or tangible assets is fundamentally misleading. We find that such asset selection schemes do not create diversification benefits, whether refer-

ence portfolios are structured by traditional asset classes or factor exposures.

We conclude that in general, what is typically referred to as listed infrastructure, defined by SIC code and industrial sector, is not an asset class or a unique combination of market factors, but instead cannot be persistently distinguished from existing exposures in investors’ portfolios, and that expecting the emergence of a new or unique ‘infrastructure asset class’ by focusing on public equities selected on the basis of industrial sectors is misguided.

Figure 2 provides an illustration of these results in the case of the FTSE Macquarie Listed Infrastructure index for the US market.

Thus, asset owners and managers who use the common ‘listed infrastructure’ proxies to benchmark private infrastructure investments are either misrepresenting (probably over-estimating) the beta of private infrastructure, and usually have to include various ‘add-ons’ to such approaches, making them completely ad hoc and unscientific.

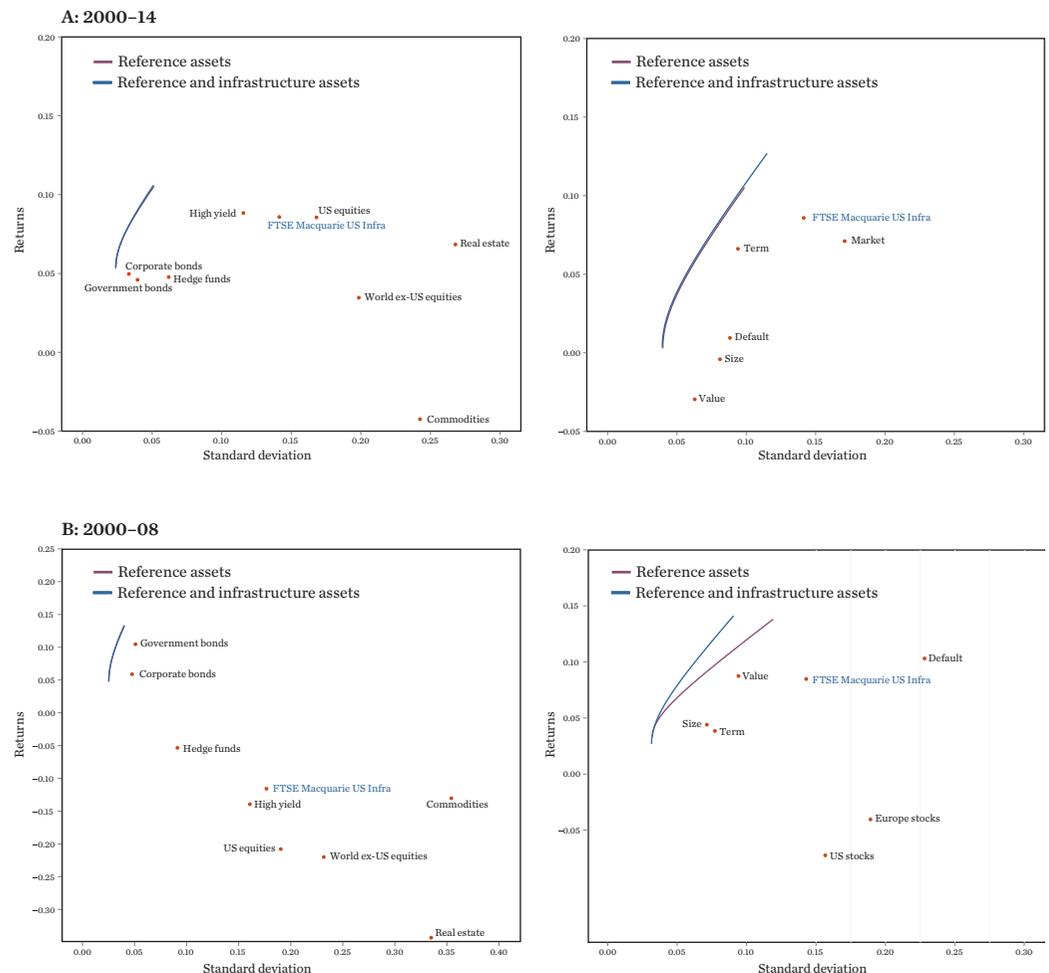
Defining infrastructure differently

Our tests also tentatively suggest a more promising avenue to ‘find infrastructure’ in the public equity space: focusing on underlying contractual or governance structures that tend to maximise dividend payout and pay dividends with great regularity, such as the public-private partnerships (PPPs) or master limited partnerships (MLPs) models, we find that the mean-variance frontier of a reference investor can be improved.

The answer to our initial question this partly depends on how infrastructure is defined and understood as an asset selection scheme.

Under our third definition of infrastructure, which focuses on the relationship-specific

2. Asset class and factor-based reference



◀ and contractual nature of the infrastructure business, we find that listed infrastructure may help identify exposures that have at least the potential to persistently improve portfolio diversification on a total return basis. This effect is driven by the regularity and the size of dividend payouts compared to other corporations, infrastructure or not.

What determines this ability to deliver regular and high dividend payouts is the contractual and governance structure of the underlying businesses, not their belonging to a given industrial sector. Bundles of PPP project companies or MLPs behave differently than regular corporations – ie, their ability to retain and control the free cash flow of the firm is limited and they tend to make large equity payouts. In the case of PPP firms, as Blanc-Brude, Hasan, and Whittaker (2016) show, they also pay dividends with

much greater probability than other firms.

In other words, going beyond sector exposures and focusing on the underlying business model of the firm is more likely to reveal a unique combination of underlying risk factors.

However, it must be noted that the relatively low aggregate market capitalisation of listed entities offering a ‘clean’ exposure to infrastructure ‘business models’ as opposed to ‘infrastructure corporates’ may limit the ability of investors to enjoy these potential benefits unless the far larger unlisted infrastructure fund universe has similar characteristics.

Future work by EDHEC*infra* aims to answer these questions in the years to come.

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