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INTRODUCTION

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

In our first 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. Our study suggests a meaningful new dynamic approach, which consists of treating attributes of stocks as instrumental variables to estimate betas with respect to risk factors for explaining notably the cross-section of expected returns.

In our second article, we provide a broad overview of initiatives to launch new forms of alternative indexes based on the market value of debt, which can be broadly classified into two different categories — fundamental approaches and diversification approaches. Our main conclusion is that none of the approaches successfully addresses all the key concerns and challenges involved in designing a truly investor-friendly bond benchmark.

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. 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.

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. 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 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.

We introduce a new approach with the objective of maximizing 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 indexes 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 toward 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. 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 what is typically referred to as listed infrastructure is not an asset class or a unique combination of market factors.

We trust that you will find the articles in the supplement insightful. We wish you an enjoyable read and extend our warmest thanks to Pensions & Investments for their continuing support.
In investment practice, multi-factor models have become standard tools for the analysis of the risk and performance of equity portfolios. On the performance side, they allow abnormal returns (or alphas) to be disentangled from the returns explained by exposure to common, or macro, risk factors. On the risk side, they allow for a subdivision between specific and systematic risk, whether one considers volatility or the tracking error with respect to a benchmark.

Many of the common risk factors used in equity portfolio management are constructed from macroeconomic attributes and reflect empirical patterns recurrently found in equity returns, such as the outperformance of small stocks over large ones (Fama, 1981), of value stocks over growth stocks (Fama and French, 1992) and of past recent winners over past losers ( Jegadeesh and Titman, 1993). A common explanation for these effects, which are anomalies for the CAPM of Sharpe (1964), is that the size and the value premia are rewards for exposure to systematic sources of risk not captured by the market factor. This is the motivation for the introduction of the size and value factors by Fama and French (1993), and for the momentum factor by Carhart (1997). More recently, the approach has been extended to investment and profitability factors, with Fama and French (2015) sorting stocks on operating profit or sales over their total assets, and Hou, Xue and Zhang (2015) replacing the former measure by the return on equity. In this process, observable attributes 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.

But the standard practice of treating attributes as factors severely increases the number of factors to consider, given the number of possible 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 micro attributes.

In theory, risk and performance of a portfolio can be explained by a combination of several such dimensions, and the question is how to assess, for example, what the marginal contributions of various sectors are in addition to stock-specific attributes to the performance and risk of a given equity portfolio. The fundamental factor 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 $\beta_{0,i}$ and $\beta_{1,i}$ 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 is described by the same equations as the previous one, but the intercepts $\beta_{0,i}$ and $\beta_{1,i}$ are functions of the sector, as opposed to being stock-specific.

The model can be used to decompose the expected return and the variance of a portfolio conditional on the current weights and constituents’ characteristics. 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 the three continuous attributes. In Exhibit 1, we show an application of this method to the analysis of the expected return of a broadly equally weighted portfolio of U.S. stocks.

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 capitalization has a negative impact on both alpha and market exposure, confirming that large caps tend to have smaller abnormal performance and market exposure.

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. The motivation is that the fundamental beta is an explicit function of the most recent values of the stock’s characteristics, and, as such, should be a more forward-looking measure of market exposure than the rolling-window one, which is a function of past returns.

In order to achieve more robustness in the results, we repeat the comparison for 1,000 random universes of 30 stocks picked among the 218 that remained in the S&P 500 universe between 2002 and 2015. We compute the two market-neutral portfolios in each universe, and we compare the market beta...
over the entire period to one, so as to assess their respective degrees of market neutrality.

Exhibit 2 shows that portfolios based on fundamental beta achieve, on average, better market neutrality than those based on time-varying historical beta, with an in-sample beta of 0.925 vs. 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 beta, vs. 0.862 for the portfolios based on historical time-varying beta.

Not only does the fundamental beta perform better on average, but it also improves the worst case deviations from the target of a unit beta. Indeed, it turns out that the historical method generally exhibits the largest deviations, with a number of dates (such as March 1996, December 2005 or March 2007) where the relative difference exceeds 60%! In comparison, the fundamental method leads to much lower extreme differences.

Fundamental betas and the cross-section of expected returns

The 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, in which the conditional beta is the fundamental beta, is more successful, by using the method of Fama and MacBeth (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.

We test two versions of the fundamental CAPM, respectively with a constant and 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, 1990), Hodrick (1992) and Mercul, 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 Exhibit 3, we compare the distributions of alphas across the 30 portfolios for four asset pricing models. These results suggest that the fundamental 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 reduced from 5.04% down to 1.69%. Remarkably, this model performs as well as the Fama-French-Carhart model, which uses four factors and is thus less parsimonious.

Accounting for the time variation in the conditional market premium also proves to be an effective way of improving the ability of the fundamental CAPM to explain the cross-section of expected returns. Furthermore, the average alpha obtained with this model is much lower than the one obtained with Fama-French-Carhart model, suggesting that additional ad-hoc factors are not necessary to achieve a satisfactory ex- planatory power.

Interestingly, this approach can be extended in a straight-forward manner from a single-factor model to a multi-factor model, thus allowing exposure to a variety of underlying systemic macro factors to depend upon the micro characteristics of the firm.

The research from which this article was drawn was produced as part of the CACEIS “New Frontiers in Risk Assessment and Performance Reporting” research chair at EDHEC-Risk Institute.

References


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

A number of concerns have been expressed about the (ir)relevance of existing forms of corporate and sovereign bond indexes offered by index providers (Reilly and Wright, 2006). One of the major problems with bond indexes 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 indexes will have a tendency to overweight bonds with large amounts of outstanding debt. It is often argued that such indexes will thus give too much weight to riskier assets. While it is debatable whether debt-weighting really leads to the most risky securities being overweighted, it is clear that market-value-weighted debt indexes lead to concentrated portfolios that are in opposition with investors’ needs for efficient risk premia harvesting, which involves holding well-diversified portfolios. In a nutshell, a good case can be made that existing bond indexes tend to be poorly diversified portfolios, regardless of whether or not the overweighting applies to the wrong constituents. A similar problem has been documented for equity indexes — 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 indexes) 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 indexes can be regarded as more “labor-intensive” than “investor-friendly,” in the sense that these bond indexes 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 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 an overview of these initiatives, which can be broadly classified in 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 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 (e.g., 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 indexes using exclusively GDP measures to adjust the weights allocated to various regions, with methodological details varying across different providers. All these indexes are compared 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 indexes deals with only one drawback of cap-weighted indexes, 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 indexes address correlation 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 example, 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 U.S. Corporate Aaa-A Capped Index is market-cap weighted with a 3% cap).

Extending the concept, equally weighted indexes, 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 indexes 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 U.S., and with an outstanding value of at least $500 million) are classified into one

1 See also Bally, Ken and Wright (1992) for an early analysis of bond indexes.

2 A higher weight for an issuer with a high market value of debt does not necessarily mean that the index is over-weighting 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 one answer onto issuers would not be a problem if riskiness is rewarded by higher expected returns.

3 We do not discuss here the liability-driven approaches such as the Market-Index US Pension Liability Indexes, 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.
Fundamental indexing in the bond market is a direct transfer of methodologies originally developed for equities.

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 indexes 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 indexes, 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 indexes, 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 indexes 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 optimization 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 vs. an optimally chosen combination on the basis of careful parameter estimates. The notion that 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 maximizing 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 optimization 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 1 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 (e.g., 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 2 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 curve) 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 maximization 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) maximization, we also test different heuristic portfolio optimization 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 benchmarking models that will provide adequate answers to investors’ needs. The contribution in this supplement by Riccardo Rebonato entitled “Are Smart Beta Strategies Appropriate for the Fixed Income Asset Class?” will provide a wealth of useful insights with respect to the benefits and challenges associated with risk premia harvesting in fixed-income markets.

References


Are Smart Beta Strategies Appropriate for the Fixed Income Asset Class?

In the last decade, the search for priced non-market 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-capitalization weighting schemes).

Recently, this focus has been shifted to other asset classes (see, e.g., Asness, Moskowitz and Pedersen, 2013) and to fixed income in particular. Given the huge size of the fixed-income market, 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-sectional analyses of risk premia;
• we explain the various questions answered in the equity space, these strategies permit the construction of more desirable portfolios than naive passive allocations (such as equal or market-capitalization weighting schemes);
• 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-sectional analyses of risk premia;
• we explain the various questions answered in the equity space, these strategies permit the construction of more desirable portfolios than naive passive allocations (such as equal or market-capitalization weighting schemes);
• we explain the unique challenges encountered in identifying priced risk factors in fixed-income products and present the main findings obtained to date.

The question arises as to whether smart beta strategies will prove effective for the fixed-income asset class.

We explain the various questions answered in the equity space, these strategies permit the construction of more desirable portfolios than naive passive allocations (such as equal or market-capitalization weighting schemes).

By time-series and cross-sectional analyses of risk premia, these empirical studies said, not tout court jettisoned. These empirical studies were silent, however, as to the nature of the additional factors. It is reasonable to accept the existence of non-market factors? If 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 labor income; inflation would erode the purchasing power of their consumption. If this were true, high and low consumption would indeed only be linked to the performance of the market portfolio.

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. This, in turn, motivated, or at least provided the theoretical justification for, the empirical search of non-market factors.

In parallel, studies in behavioral finance and in the institutional workings of financial markets pointed on the one hand to the bounded rationality of investors, 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 of 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, ri, over the riskless rate, rf, from security i, on the market excess return, rm − rf,

\[ r_i - r_f = \alpha_i + \beta_i (r_m - r_f) + \epsilon_i \]  

(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, αi, 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, xi, such that

\[ r_i - r_f = \alpha_i + \beta_i (r_m - r_f) + \sum_{k=1}^{n} \beta_k x_i + \eta_i \]  

(2)

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

\[ \sum_{k=1}^{n} |\beta_k x_i| < \sum_{k=1}^{n} |\alpha_k| \]  

(3)

In the equation above, the quantities wi 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 αi in Equation (1)) into new interpretable “betas” (the βi 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 αi. In their early work they identified, in addition to the market portfolio, two additional factors: the small-minus-big factor, 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). 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, 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 rigor and statistical robustness

8 According to the BIS, the size of the global debt market is approximately $220 trillion (as reported in the Financial Times, November 10, 2016, page 18, Lex).
9 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,” Arg (2016), page 197; emphasis added. See also Welch (2008) and Graham and Harvey (2001); quoted therein.
10 Arg (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.
11 The first to include macro factors in equities in the cross-sectional search for systematic source of risk were Chen, Roll and Ross (1986).
12 and to the difficulty to attribute these rationalities away (see, e.g., Shleifer and Vishny, 1997).
13 More precisely, the Fama and French factors were factor-mimicking portfolios, i.e., long-short portfolios of stocks that would mimic the factors of interest.
14 For instance, the VIX index is an obvious proxy for volatility risk.
of these studies varied greatly.11 So, alongside the factors that traditional asset pricing theory would readily understand, a richly populated menagerie of more opaque “anomalies” was born.12 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 capitalization were soon created in the equities arena that would tilt the portfolio composition toward 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 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 reported. Since in the old CAPM world the only way to gain extra unleveraged return was to increase the degree and nature of the weight tilt would be determined in such a way as to exploit diversification in order 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 reported. Since in the old CAPM world the only way to gain extra unleveraged return was to increase the exposure to the market capitalization were soon created in the equities arena that would tilt the portfolio composition toward the non-market rewarded factors.

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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 focused on (mainly U.S.-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% of 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 program that until very recently was their staple diet of risk-premium research in fixed income can be summarized 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-returns on a fixed-income bond of maturity $t$, $P_t$, are given by

$$E[P_t|P_0] = P_0 - \left( r + \frac{1}{t} \sum \delta P_t \sigma_t \right) dt$$

where $\sigma_t$ is volatility of the $t$-th factor and $\lambda_t$ its associated market price of risk. If the “market prices of risk” are assumed to depend on the state variables, $\lambda_t = \lambda(x_1, x_2, \ldots, x_n)$, the search for time- (state-) dependent risk premia boils down to:

- 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 structural (see, e.g., Kim-Wright (2005), or Adrian, Crump and Moench (2014, 2015)) models.

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, e.g., 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 last 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

The Fixed-Income landscape for Developed Markets (DM)

11 As Fama famously said, abandoning the requirement to link a factor to a cogent consumption story was equivalent to issuing a “fishing license.” 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, e.g., Abu-Mostafa, Magdon-Ismail and Lin (2012) in this respect.

12 The distinction between “true” risk factors and “anomalies” is not a purely academic one, as they remain the market compensation for receiving large payoffs in good states of consumption, and vice versa. Behaviorally driven irrationalities, instead, may be corrected by sufficiently well capitalized arbitrageurs (such as hedge funds), and as for institutional frictions, these can disappear at the stroke of a regulatory pen.
it has been claimed that efficient portfolios can be built by reducing exposure to corporates or sectors with large issuance size.

which are shown in Exhibit (1) (which only looks at Developed Market, DM).

As the picture 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 somewhat different instruments to risk,
• real and nominal bonds (which come in government and corporate flavor),
• funded and unfunded (i.e., cash vs. swap) instruments,
• corporates for which public data are available (and for which accountancy-related characteristics can be extracted) and corporate for which this is not possible.

Securitized 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, e.g., Collins-Dufresne, Goldstein and Martin (2001)), both the theoretically motivated variables13 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 amount of idiosyncratic risk.

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.

Howing 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 imperfect, 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 return comparable to, if not higher, the 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. For as “excessive” an issuer 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 2005–2006). 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 BTNs 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 work with momentum, complicating the analysis.

Value has been found to be 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/cheap 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 behavioral theories, while the high Sharpe Ratios of a global diversified 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.

CONCLUSION

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, how to “transliterate” from one asset class to another often requires careful handling.

A convincing economic interpretation of the factors still 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.

References


13 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.
The Impact of Costs on Smart Beta Strategies

Mikheil Rkasuk, Head of Quantitative Research, ERI Scientific Beta

An important issue with smart beta strategies is that they typically entail higher replication costs than cap-weighted market indexes. While this is obviously true, the crux of the question is 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 in order 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 data 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 become 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 analyze 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 analyze 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 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 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 use our cost estimates to range of smart beta strategies to draw conclusions about cost levels, it is worth emphasizing 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

The following exhibit 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 capitalization (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 spread 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 (i.e., 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 U.S. 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 one-eighth to one-sixteenth, and the second major reduction occurred in 2001 when the tick size went from one-sixteenth to one-hundredth (i.e., decimalization). 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.

Analyzing 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 summarize and illustrate below.

Transaction costs and implementation challenges crucially depend on the stock universe

First, we find that conclusions about transaction cost levels and strategy implementation challenges are heavily dependent on the stock universe used. While it is common to see broad brush statements about incentivization 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 incentivization 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 analyze 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.

These results underline the importance 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 annualized transaction costs is 0.13% 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 investibility 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 stylized 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 Exhibit 3) 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 annualized transaction costs change from 0.38% to only 0.18% and investibility measures such as days-to-trade go from 3.14 to 2.19 when applying practical implementation 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 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 indexes 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 indexes 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 indexes. 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 annualized transaction costs over the 42-year period are between 0.13% to 0.18%, while gross returns relative to the cap-weighted index range from 2.38% to 3.93%. The following exhibit shows five-year rolling window returns, both net and gross returns. For brevity, the graphs show the average return across the three strategies analyzed.

Managing switching costs into smart beta strategies

Another aspect that is important to analyze 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 indexes to smart beta strategies in a straightforward way by stretching out the transition from a cap-weighted portfolio to...
Rolling Window Analysis (Average across three Strategies; USA Long Term Track Records)
The exhibit presents the average annualized 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 indexes each year are plotted. The time period of analysis is Dec. 31, 1972, to Dec. 31, 2014. All statistics are annualized and daily total returns in USD 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 costs are the difference between the annualized 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.

Comparison of stretched and non-stretched transition from Cap-Weighted portfolio to Smart Beta Portfolio (Long Term — 42 years)
The time period of analysis is Dec. 31, 1972, to Dec. 31, 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 i.e. 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 i.e. 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) transition is computed quarterly and average is reported. Difference in Gross Returns is computed quarterly between stretched (both 10-days and 20-days) and non-stretched transition. All statistics reported in Panel B are annualized. It compares costs of all three smart beta strategies. Assuming 10-year investment period, the Annualized 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). Annualized Cost of Rebalancing is the average difference between annualized gross and net returns. Total Annualized Cost is sum of transition and rebalancing costs.

### Exhibit 4

**Panel A: Transition from Cap-Weighted Index (statistics for transition quarter)**

<table>
<thead>
<tr>
<th>Days to Trade (95%tile)</th>
<th>Non-stretched</th>
<th>Stretched 10-days</th>
<th>Stretched 20-days</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transition</td>
<td>1.72</td>
<td>0.17</td>
<td>0.09</td>
</tr>
<tr>
<td>Efficient Minimum Volatility</td>
<td>1.98</td>
<td>0.20</td>
<td>0.10</td>
</tr>
<tr>
<td>Maximum Deconcentration</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Multi-Beta Multi-Strategy (4-Factor EW)</td>
<td>2.64</td>
<td>0.28</td>
<td>0.13</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Tracking Error</th>
<th>Non-stretched</th>
<th>Stretched 10-days</th>
<th>Stretched 20-days</th>
</tr>
</thead>
<tbody>
<tr>
<td>Difference in Gross Returns by Stretching</td>
<td>Non-stretched</td>
<td>Stretched 10-days</td>
<td>Stretched 20-days</td>
</tr>
<tr>
<td>-0.01%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>-0.01%</td>
</tr>
</tbody>
</table>

### Exhibit 5

**Panel B: Cost Comparison**

| Annualized Cost of Transition from Cap-Weighted (assuming 10 year investment period) | 0.02% | 0.02% | 0.03% |
| Annualized Cost of Rebalancing | 0.18% | 0.13% | 0.17% |
| Total Annualized Cost | 0.20% | 0.15% | 0.20% |
a smart beta strategy. In Exhibit 5, we address both the trans-
action 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 esti-
mates to the trades needed to switch from the cap-weighted
index to the smart beta index and compute the correspon-
ding annualized 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 in-
crease 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. •

CONCLUSION
The results of our research provide an important contri-
bution 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 often relies on simulated gross returns. On the
other hand, discussion of cost issues more often than not re-
mains at the level of blanket criticism aimed at certain strate-
gies, 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. Im-
portantly, given the transparent methodology and benign
data needs, our replication cost analysis is straightforward and
can be easily applied to other strategies.

EXHIBIT 2
Implementation Costs of Generic Alternative Weighting Schemes (USA Long Term Track Records (LTTR) — Long
Term — 42 Years)
The time period of analysis is Dec. 31, 1972, to Dec. 31, 2014. All statistics are annualized and daily total returns in USD are used for
this analysis. From the 3,000 largest stocks in the USA, 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

<table>
<thead>
<tr>
<th>Number of Stocks in the Universe</th>
<th>U.S. Long Term 31-Dec-1972 to 31-Dec-2014</th>
</tr>
</thead>
<tbody>
<tr>
<td>250</td>
<td></td>
</tr>
<tr>
<td>500</td>
<td></td>
</tr>
<tr>
<td>1000</td>
<td></td>
</tr>
<tr>
<td>3000</td>
<td></td>
</tr>
<tr>
<td><strong>Transaction Costs</strong></td>
<td><strong>Number of Stocks in the Universe</strong></td>
</tr>
<tr>
<td>Cap-Weighted</td>
<td>0.04%</td>
</tr>
<tr>
<td>Equal-Weighted</td>
<td>0.13%</td>
</tr>
<tr>
<td>Fundamental-Weighted</td>
<td>0.11%</td>
</tr>
<tr>
<td>Days to Trade (95 %ile)</td>
<td>2.06</td>
</tr>
<tr>
<td>Cap-Weighted</td>
<td>2.06</td>
</tr>
<tr>
<td>Equal-Weighted</td>
<td>2.39</td>
</tr>
<tr>
<td>Fundamental-Weighted</td>
<td>2.83</td>
</tr>
</tbody>
</table>

EXHIBIT 3
Impact of Turnover and Liquidity Rules on Minimum Volatility Strategy
The time period of analysis is Dec. 31, 1972, to Dec. 31, 2014. All statistics are annualized and daily total returns in USD are used for
this analysis. Data Source: CRSP, Scientific Beta

<table>
<thead>
<tr>
<th>USA LTR 31-Dec-1972 to 31-Dec-2014</th>
<th>Efficient Minimum Volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td>Before Turnover</td>
<td>After Turnover but</td>
</tr>
<tr>
<td>Before Liquidity Rules</td>
<td>After Turnover and</td>
</tr>
<tr>
<td></td>
<td>Liquidity Rules</td>
</tr>
<tr>
<td>One-Way Turnover</td>
<td>54.57%</td>
</tr>
<tr>
<td>Transaction Costs</td>
<td>37.96%</td>
</tr>
<tr>
<td>Days to Trade (95 %ile)</td>
<td>30.02%</td>
</tr>
<tr>
<td>Trading Multiple (99 %ile)</td>
<td>30.02%</td>
</tr>
</tbody>
</table>

The research from which this article was drawn was produced
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Passive Investment Strategies" research chair at EDHEC-Risk
Institute.

References

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.
INDEXES

Can Portfolio Rebalancing be a Source of Additional Performance?

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INDEXES

Source of Additional Performance?

Introduction

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, sometimes referred to 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.

The growth rate of a portfolio \( G_{p}(0,T) \) on the period \([0;T]\) is simply defined as:

\[
G_{p}(0,T) = \frac{1}{T} \ln \frac{P_{T}}{P_{0}}
\]

where \( P_{0} \) denotes the portfolio initial value and \( P_{T} \) its final value.

If we now consider a fixed-weight portfolio \( P_{NW} \) and a buy-and-hold portfolio \( P_{BH} \) based on holding \( n \) assets with the same initial weights \( w_{1}, \ldots, w_{n} \), then the rebalancing premium \( R_{P}(0,T) \) over the period \([0;T]\) is simply defined by:

\[
R_{P}(0,T) = \left[ E\left[G_{P}(0,T)\right] - E\left[G_{P,BH}(0,T)\right]\right] = \frac{1}{T} \ln \frac{P_{T}}{P_{0}}
\]

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.

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 90 bps (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.

EXHIBIT 1

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 portfolio.

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 1 month. Firstly, we focus in Exhibit 1 on the historical rebalancing premium as a function of time horizon (ranging from 1 month to 3 years) for different numbers of stocks in the portfolios. For a 5-year time horizon and a number \( N = 30 \), the historical rebalancing premium is reasonably high at 85 bps. In a different configuration, with a 10-year time horizon and \( N = 50 \) risky assets, the historical rebalancing premium is 113 bps. We assess that the number of stocks considered has almost no influence as long as it exceeds a minimum value around 50. This first perspective shows that the historical rebalancing premium from our S&P 500 base universe is higher than 50 bps if the number of stocks \( N \) is higher than or equal to 5 and time horizon is at least 5 years. If we take the number of stocks \( N \) higher than or equal to 10, then the historical rebalancing premium is higher than 50 bps for time horizons higher than or equal to 2 years.

Exhibit 2 shows the distribution of the difference in growth rates for a 5-year time horizon and also displays the evolution of that difference over time for the period November 1985 to December 2010. Each date on this chart corresponds to a 5-year period starting date. The analysis of the 5-year realized growth rates difference allows us to have a more precise view on all the 5-year historical scenarios and not only their average. The average growth rates difference, i.e., the historical 5-year rebalancing premium, is 86 bps. The growth rates difference achieves the highest value (higher than 100 bps) for the starting dates in the period January 1996 to January 2000 and August 2004 to October 2008, and the lowest value (lower than -50 bps) for the starting dates in the period July 2002 to March 2004. We note that among the 302 historical 5-year scenarios, 36% of them display a growth rates difference higher than 100 bps, 61% display a growth rates difference higher than 50 bps 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 capitalization, 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 characteristics 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 to December 2015 as...
Our base universe and take five possible time horizons: 1, 2, 3, 4 and 5 years. We do not consider longer horizons for a persistence criterion.

For a given characteristic (market capitalization, for instance), we build at each initial (end-of-month) date to two sets ("high" and "low") of two portfolios (1 equally-weighted and 1 buy-and-hold):
1. 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.
2. 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 analyze 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 Exhibit 3 that "market capitalization," "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 5-year rebalancing premiums of 138, 107, 131 and 125 bps when random portfolios (N=30) display on average a 5-year rebalancing premium of 85 bps. The 5-year rebalancing premium can be enhanced by more than 40 bps if stocks are selected according to a characteristic such as market capitalization rather than randomly. On the other hand, "serial correlation" as a sorting criterion does not lead to a substantially higher rebalancing premium for time horizons higher than 1 year: for instance the 5-year rebalancing premium for portfolios of stocks with negative serial correlation is 67 bps. 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 90 bps (in the absence of transaction costs) for a 5-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. 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 1 year to 5 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 indexes. 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 analyze 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.
Maximizing Exposure to Long-Term Rewarded Factors in a “Top-Down” Framework

INTRODUCTION

There are two approaches to factor investing. The first approach is a diversification strategy where the main objective is to maximize the index’s diversification power while controlling the factor exposures. This strategy corresponds to ERI 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 maximize the benefit of the exposure to long-term rewarded factors. In this case, diversification benefits and obtain maximum exposure while maintaining balance across factors and reasonable diversification levels.

The first approach is a diversification strategy (mono indexes). For each of the following five tilts, the following five weighting schemes are applied:

- Value, High Momentum, Low Volatility, High Profitability, Low Investment.
- Max Deconcentration, Max Decorrelation, Efficient Minimum Volatility, Efficient Maximum Sharpe, Diversified Risk Weighted.

Mid-cap tilted indexes are not included in the list because the mid-cap tilt, relative to broad cap-weighting, is implicitly present in the other factor-titled indexes. This is because the five weighting schemes used on each factor tilt do not concentrate the portfolio relative to cap-weighting and does 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).

\[ C_{i,k} = \frac{\text{rank}(b_{i,k})}{U} \]

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

\[ C_{j,k} = \sum_{i=1}^{U} W_{ij} C_{i,k} \]

EXHIBIT 1

<table>
<thead>
<tr>
<th>Constituent</th>
<th>Value Score</th>
<th>Momentum Score</th>
<th>Geometric Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stock-1</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Stock-2</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Stock-3</td>
<td>0.1</td>
<td>0.1</td>
<td>0.01</td>
</tr>
<tr>
<td>EW Portfolio of Stock-1 and Stock-2</td>
<td>0.5</td>
<td>0.5</td>
<td>0.25</td>
</tr>
</tbody>
</table>

Allocation methodology

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

- Value, High Momentum, Low Volatility, High Profitability, Low Investment.
- Max Deconcentration, Max Decorrelation, Efficient Minimum Volatility, Efficient Maximum Sharpe, Diversified Risk Weighted.

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 indexes representative of the selected weighting strategies, but that take account of the stocks’ residual exposures. For this reason, High Factor Exposure (HFE) filtered indexes 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, 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.” The single factor, single strategy indexes which are used here are constructed on these HFE selections.

Geometric mean score

The geometric mean score 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.

We introduce a new ERI Scientific Beta approach with the objective of maximizing exposure to the long-term rewarded factors in a “top-down” framework, in a robust and well-diversified manner.

*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 standardize the attribute values by calculating ranks as C_{i,k} = \text{rank}(b_{i,k}) / U. To reduce the variability in scores affecting the robustness of optimization, we can adopt the decimals technique in scoring that we already use in Max Sharpe Ratio optimization. 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, i.e., when the scores are assigned. This only affects the stock level scores.
where $w_{ij}$ denotes the weight of stock $i$ in index $j$. We can now construct a portfolio which combines the indexes and the k-th weighted average portfolio attribute as follows (where $w_{jk}$ denotes the weight of index $j$ in the final portfolio “solution”):

$$C_{PLk} = \sum_{j=1}^{N} W_{Pj} C_{jk}$$

**Optimization Problem**

Maximum Geometric Mean Score (Max GMS) optimization is performed with a constraint on factor scores and deconstruction. All six factor scores are constrained to be greater than the median score (0.50). Norm constraints are applied simultaneously to ensure deconstruction 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 indexes are used.

The constraint on the effective number of constituents corresponds to a typical deconcentration constraint which ensures that the solution to the portfolio optimization will not result in a portfolio which is very concentrated in few constituent indexes. 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 re-balanced semi-annually on the third Friday of June and December.

**Performance and Risk**

So far, we have seen how maximizing the geometric mean of scores affect individual factor scores. We now turn to the assessment of the performance, risk, and factor exposures of Diversified Max Factor Exposure along with portfolio weights that allocate equal-weights to both standard factor-tiled indexes and those with the High Factor Exposure filter, and make comparison with the cap-weighted index. While maximization 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 investibility measures in Exhibit 2.

In Exhibit 2, if we compare Multi-Beta Multi-Strategy Diversified High Factor Exposure (HFE MBMS-EW 6F) and Multi-Beta Multi-Strategy Diversification (MBDS-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, i.e., 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 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 Imbalance 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 GILR 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.
evenly spread out. However, the benefits from maximizing 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 indexes. As can be seen in Exhibit 3, 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).

Emphasizing a particular factor within Diversified Max Factor Exposure approach: the case of value

A key advantage of the top-down approach is 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 (i.e., 0.625 instead of 0.5). As can be observed from Exhibit 3, 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, stay as stable as they were before, as there is no increase in Factor Drift or Factor Intensity Drift. Moreover, investibility 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 indexes. Our approach of maximizing the overall factor exposure by allocating across indexes 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 emphasize stock-level differences which are subject to a lot of noise.

### References


### EXHIBIT 3

Illustration of Targeting Higher Value Exposure

The measures reported are same as those in Exhibit 2.

<table>
<thead>
<tr>
<th>EDHEC-Risk US LITR</th>
<th>Broad CW</th>
<th>Multi-Beta Multi-Strategy Diversified Max Factor Exposure</th>
<th>Targeting Higher Value Score (0.625)</th>
<th>Multi-Beta Multi-Strategy Diversified Max Factor Exposure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ann. Returns</td>
<td>11.12%</td>
<td>14.95%</td>
<td>14.89%</td>
<td></td>
</tr>
<tr>
<td>Ann. Volatility</td>
<td>17.04%</td>
<td>13.99%</td>
<td>13.88%</td>
<td></td>
</tr>
<tr>
<td>Sharpe Ratio</td>
<td>0.36</td>
<td>0.71</td>
<td>0.72</td>
<td></td>
</tr>
<tr>
<td>Max. Drawdown</td>
<td>54.31%</td>
<td>48.97%</td>
<td>48.27%</td>
<td></td>
</tr>
<tr>
<td>Ann. Rel. Returns</td>
<td>-</td>
<td>3.83%</td>
<td>3.77%</td>
<td></td>
</tr>
<tr>
<td>Ann. Tracking Error</td>
<td>-</td>
<td>6.27%</td>
<td>6.39%</td>
<td></td>
</tr>
<tr>
<td>Information Ratio</td>
<td>-</td>
<td>0.61</td>
<td>0.59</td>
<td></td>
</tr>
<tr>
<td>Outperformance Prob. (3Y)</td>
<td>-</td>
<td>80.07%</td>
<td>79.81%</td>
<td></td>
</tr>
<tr>
<td>Extreme Relative Return (95%-ile)</td>
<td>-</td>
<td>-9.41%</td>
<td>-9.26%</td>
<td></td>
</tr>
<tr>
<td>Extreme Tracking Error (95%-ile)</td>
<td>-</td>
<td>12.67%</td>
<td>12.66%</td>
<td></td>
</tr>
<tr>
<td>Max. Rel. Drawdown</td>
<td>-</td>
<td>41.51%</td>
<td>41.60%</td>
<td></td>
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<tr>
<td>Ann. Unexplained</td>
<td>0.00%</td>
<td>1.86%</td>
<td>1.77%</td>
<td></td>
</tr>
<tr>
<td>Market Beta</td>
<td>1.00</td>
<td>0.97</td>
<td>0.97</td>
<td></td>
</tr>
<tr>
<td>SMB Beta</td>
<td>0.00</td>
<td>0.17</td>
<td>0.18</td>
<td></td>
</tr>
<tr>
<td>HML Beta</td>
<td>0.00</td>
<td>0.22</td>
<td>0.18</td>
<td></td>
</tr>
<tr>
<td>MOM Beta</td>
<td>0.00</td>
<td>0.06</td>
<td>0.06</td>
<td></td>
</tr>
<tr>
<td>Low Vol Beta</td>
<td>0.00</td>
<td>0.11</td>
<td>0.12</td>
<td></td>
</tr>
<tr>
<td>High Prof Beta</td>
<td>0.00</td>
<td>0.12</td>
<td>0.08</td>
<td></td>
</tr>
<tr>
<td>Low Inv Beta</td>
<td>0.00</td>
<td>0.08</td>
<td>0.13</td>
<td></td>
</tr>
<tr>
<td>R Squared</td>
<td>100.00%</td>
<td>93.55%</td>
<td>93.33%</td>
<td></td>
</tr>
<tr>
<td>Factor Intensity</td>
<td>0.00</td>
<td>0.76</td>
<td>0.75</td>
<td></td>
</tr>
<tr>
<td>Factor Imbalance</td>
<td>-</td>
<td>43.02%</td>
<td>37.76%</td>
<td></td>
</tr>
<tr>
<td>Factor Drift</td>
<td>-</td>
<td>0.22</td>
<td>0.22</td>
<td></td>
</tr>
<tr>
<td>Factor Intensity Drift</td>
<td>-</td>
<td>30.26%</td>
<td>30.36%</td>
<td></td>
</tr>
<tr>
<td>Geometric Mean Score</td>
<td>0.44</td>
<td>0.59</td>
<td>0.59</td>
<td></td>
</tr>
<tr>
<td>Ann. One-Way Turnover</td>
<td>2.42%</td>
<td>54.41%</td>
<td>56.98%</td>
<td></td>
</tr>
<tr>
<td>Capacity (m$)</td>
<td>52,284</td>
<td>12,574</td>
<td>12,622</td>
<td></td>
</tr>
<tr>
<td>Effective Number of Stocks</td>
<td>122</td>
<td>1.58</td>
<td>1.53</td>
<td></td>
</tr>
<tr>
<td>GLR Measure</td>
<td>25.76%</td>
<td>29.69%</td>
<td>20.64%</td>
<td></td>
</tr>
<tr>
<td>Idiosyncratic Risk</td>
<td>-</td>
<td>3.54%</td>
<td>3.57%</td>
<td></td>
</tr>
<tr>
<td>Residual Sharpe Ratio</td>
<td>-</td>
<td>0.53</td>
<td>0.49</td>
<td></td>
</tr>
<tr>
<td>Volatility Reduction compared to Multi-Factor Benchmark</td>
<td>-</td>
<td>-2.97%</td>
<td>-2.73%</td>
<td></td>
</tr>
</tbody>
</table>
In light of increasing investor interest in multi-factor securities, 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 favored 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 specialized 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 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 scores justify additional performance that makes it worthwhile for most investors to forsake the simplicity, transparency and flexibility of "top-down" approaches. However, as outlined 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 investibility 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 wise to consider 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 overexploitation 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" vs. "top-down" debate relates to two factor investing approaches. The first, which supports the "bottom-up" approach, is where the objective of maximizing 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 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 indexes, with those of diversification, Scientific Beta is proposing an evolution of its smart factor indexes offering practitioners a high level of factor exposure while reducing the conditionality of performance. 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 overexploitation 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. The approach to factor investing that maximizes 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.

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exposures in multi-factor combinations, and we thus term these filtered indexes “diversified high factor exposure smart factor indexes.”

The multi-factor metric chosen is the arithmetic average of the normalized 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 capitalizations that is not diluted by blending smart factor indexes targeting different factors.

Diversified high factor exposure smart factor indexes, in addition to achieving the desired factor tilts by way of the initial selection, will thus also have aggregate exposures to the other rewarded factors that will be higher than that of their unfiltered counterparts. This will mitigate dilution when indexes targeting different factors are blended.

Exhibit 2 below presents the construction methodology of smart factor indexes 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 indexes, 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, i.e., 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 normalized ranks of each individual factor. The smart factor indexes 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 indexes, 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 indexes to maximize the portfolio’s geometric average exposure to the targeted factors — the multi-beta multi-strategy diversified max factor exposure index. The data on these indexes 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 Exhibit 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 indexes cancel half of the performance differential between the unfiltered “top-down” strategy and the narrow-selection score-weighted indexes 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 (4.37%) and the highest information ratio (0.65). The “top-down” approach that allows for the highest concentration to maximize the composite factor score at the portfolio level exhibits the

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<td>Based on daily total returns in USD from Dec. 31, 1975, to Dec. 31, 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 (Losers) portfolios are capital-weighted portfolios of the top (bottom) 5% and 10% stocks selected based on a multifactor score that is either the geometric mean of the six individual factors scores or the arithmetic mean of the six individual factor scores. The individual factor scores of each stock are the normalized rank scores of the stocks toward the corresponding factor variable. Factor Intensity Drift is the standard deviation of Factor Intensity Coefficients and is reported in relative terms, i.e., 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.</td>
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<td>Annualized Relative Return</td>
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<td>40% OF THE 50% FACTOR INTENSITY IS EXCLUDED BASED ON THE MULTI-FACCTOR SCORE</td>
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<td>HFE FILTERED SMART FACTOR INDICES (30% REMAINING STOCK)</td>
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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% vs. 17.43% on average, i.e., an improvement of almost 40%). Similarly, “top-down” approaches have less punishing extreme relative returns (-8.18% vs. -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 Exhibit 4 highlight some of the concentration and investibility 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 overemphasize 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 score-based limits have persisted. 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 indexes 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 capitalization-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 contagion 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-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 unwanted risks is likely to prove inefficient.

The figures in Exhibit 5 on long-term factor exposures confirm the use of diversified high factor exposure ratio factor indexes delivers “top-down” multi-factor portfolios that display significantly increased factor exposures; unsurprisingly, the diversified max factor exposure index delivers 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 leveraged 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.

The exhibit 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 indexes. 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 underappreciated 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.

### References


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Results of Institutional Investor Survey on Infrastructure Investment

Frederic Blanc-Brude
Director, EDHECinfra

Grace Chen
Senior Relationship Manager, EDHECinfra

Tim Whittaker
Associate Research Director, EDHECinfra

• 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 fund), 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).

INDEXES

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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 fund), 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 — 22.5%), investment (Head of Infrastructure, investment director — 46.2%) or other (14.5%) functions of the organizations they represent.

Infrastructure is popular. Almost two-thirds of the 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, amongst investors and also between asset owners and managers.

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

Investment beliefs

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

1. There is wide disagreement amongst 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.

2. 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.

3. 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.

4. Investors and managers define infrastructure in terms of long-term contractual arrangements and monopoly regulation and acknowledge that industrial sectors are a less informative way to categorize 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.

5. Expected returns follow a clear pattern determined by the “business model” (contracted, merchant or regulated) and the life-cycle stage (brownfield vs. greenfield), whereas higher expected returns than brownfield regulated and contracted infrastructure.

6. Despite viewing infrastructure as characterized 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 the reported returns required by investors for 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.

7. 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. 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 higher infrastructure investments rely on contracts (when it belongs to the “contracted” business model) and in the long-term (i.e. 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 homogeneity of views around these fundamental building blocks. Different types of asset owners tend to report different preferences and views are also highly homogenous between institutional investors of the same type.

What investors require a range of returns for comparable risk profiles (i.e., 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 or LPs) and general partners (GPs) which we discuss at length below.
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.

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:

1. The immense majority of asset owners are rather dissatisfied with existing infrastructure investment products.
2. 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.
3. Even co-investment alongside managers or banks is considered by almost half of asset owners to be only a second-best option, i.e., they would rather have access to the investment products they need and want.
4. The immense majority of asset owners consider the classic closed-ended private-equity infrastructure fund model to be "outdated" and "not adding value."
5. 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."
6. 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.
7. 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.
8. 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 amongst the highest-ranked objectives that are intuitively associated with infrastructure assets.

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

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be a much newer theme, can be described as “passive.” 17

For engaged investors to be better off following 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 investing are thus determined by three factors:

1. Investment costs: with limited effects of competition between managers on fees, some asset owners have come to the conclusion that internalizing infrastructure investment can be worthwhile. Nevertheless, a fully fledged infrastructure team is only available to large investors. Such teams may also encounter the “lifecycle” issues as investors buy infrastructure firms (transaction structuring and execution) and operate them on a buy-and-hold basis (asset 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 recreated internally between the strategic asset allocation level and the investment level.

2. 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 (i.e., 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 the fact that a growing number of large investors prefer forgoing diversification benefits in favor of a more concentrated, internally-managed portfolio.

3. 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 internalizing 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 signaling

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, 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

17 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.

18 The infrastructure asset.
of DIY investing and the Charybdis of infrastructure PE funds. There are, however, solutions to minimize 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.

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

In economics, this problem is typically modeled 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, Shiner 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:

1. 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.
2. 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.
3. 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 up front, including the requirement to collect information known to exist in a reasonably standardized format and limited to what is necessary to implement robust asset pricing and risk models. It puts forward the following steps:

1. Defining the relevant instruments
2. Developing a relevant asset pricing framework
3. Defining the necessary data
4. Building a global database of cash flows and investment characteristics
5. 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 infra-
structure investment are usefully defined, the second neces-
Sary 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 ur-
gent 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.

A two-step approach to measuring performance is therefore
necessary.

1. Documenting cash flow distributions (debt service and
dividends) to address the fundamental problem of unob-
orable or insufficiently reported NAVs or losses given
default (LGDs).

2. Estimating the relevant (term structure of discount rates,
or required 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 ac-
count the complexity of the projects, while applying the best-in-class models of financial performance measurement (see, for ex-
ample, Blanc-Brude, Hasan, and Ismail (2014) and Blanc-
and Hasan (2015) for applications to the private debt and equity case).

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

The active collection of the necessary data and publica-
tion of the relevant investment benchmarks has begun to be im-
plemented 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 signaling

Market forces have changed before, asset owners highlight high fees, insufficient performance reporting and inadequate valuation methods as some of the main issues found in del-
egated private investment.

In recent years, however, asset owners have begun to ques-
tion the level of investment fees and to achieve substantial reduc-
tions in the overall level of investment management fees, through
self-organization as well as with the help of the regulator.

As we argued above, high fees are only the result of the in-
formation asymmetry that exists between asset owners and
managers. The crux of the matter hinges around reported val-
uations. The valuation of private assets is the primary source of
information asymmetry between managers and asset own-
ers. Hence, with the argument to lower fees gradually being
won by LPs, the next big issue to open for review is asset
valuation.

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 ap-
plied to infrastructure). As we suggested above, a number of tech-
niques based on market measures, risk-adjusted performance, and other measures of risk-adjusted performance in private infra-
structure 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
allowing state-of-the-art valuation methodologies is also re-
levant to the “sorting mechanisms” or “signalling” that we dis-
cussed 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 ca-
pable 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 ad-
ap a different and therefore better 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 be-
comes possible for the latter to require that they exert the
kind of effort that should lead to the creation of better invest-
ment 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
dead — the incentive compatible contract between the man-
der 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 internalization — the DRY option — re-
names the preferred route).

Beyond type revelation or discovery, the last missing el-
ement in the relationship between principal and agent is for
asset owners to actually know what to ask the better man-
gagers to do 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
(e.g., what combination of factor exposures infrastructure in-
vestment can create) and only then can asset owners require
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 de-
termine what investors should require and to signal what man-
gagers can or cannot deliver.

ESG

Regarding the environmental, social and governance impact
of infrastructure investment, asset owners’ responses suggest that
1. Investors acknowledge the relevance of ESG considerations but a majority considers ESG to be a second-order problem, i.e., one that does not trump first-order questions like strategic asset allocation.
2. Nevertheless, 17% of owners consider ESG to be a first-order question.
3. Most respondents also expect ESG to be positively related to investment returns.

Does ESG mean more or less risk?

Institutional investors have all well-defined mandates to
for instance, ensure the delivery of pension benefits, the sol-
licity 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 hori-
zons and preserving the funding level (liabilities vs. 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 infrastructure projects (e.g., coal-fired power plants) or ensure that the social consequences of new projects (e.g., hydroelectric dams) are limited and well man-
aged, the considerations must nevertheless remain subordi-
nated to achieving long-term financial objectives.

It does not mean that investors “do not care” about in-
vesting 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 the survey.

ESG investing can be modelled as a form of “quilt asso-
ciation” — a notion developed in behavioral economics — by
which investors could be willing to forgo some level of per-
formance 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, a majority of respondents believe that there is a posi-
tive 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 posi-
tive 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. Re-
cent 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 in-
vestments is job creation. While this can be considered a posi-
tive in regards to the social and political acceptance of private
infrastructure investment (the so-called “social license to oper-
ate” 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 sev-
eral decades. The impact of contaminizer 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 in-
vestments, it may be interpreted as an increase in risk aver-
sion vis-a-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.

References


Blanc-Brude, Frédéric, Majid Hasan, and Omneia R H Ismail. 2014. “Data Collection for Infrastructure Investment Benchmarking: objectives, Re-
ality Check and Reporting Framework.” EDHEC Infrastructure Institute-Singapore.

Blanc-Brude, Frédéric, Majid Hasan, and Omneia R H Ismail. 2014. “Unlisted Infrastructure Debt Val-
uation & Performance.” EDHEC-Risk Institute Publications, EDHEC and NATIXIS Research Chair on In-


Hallwege, Martin. 1987. “Some Recent Developments in the Theory of Competition in Markets with Ad-


Is Listed Infrastructure an Asset Class in its own Right?

<table>
<thead>
<tr>
<th>Frederic Blanc-Brude</th>
<th>Tim Whittaker</th>
<th>Simon Wilde</th>
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<tbody>
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<td>Director, EDHECinfra</td>
<td>Associate Research Director, EDHECinfra</td>
<td>Research Associate, EDHECinfra</td>
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We ask whether focusing on listed infrastructure stocks creates diversification benefits previously unavailable to large investors that are already active in public markets. This question arises from what we call the "infrastructure investment narrative" (Blanc-Brude, 2012), 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.

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:
1. A "naive," rule-based filtering of stocks based on industrial sector classifications and percentage income generated from pre-defined infrastructure sectors (nine proxies);
2. Existing listed infrastructure indexes designed and maintained by index providers (12 proxies).

Empirically, there are at least three reasons why this view requires further examination:
1. 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.
2. Index providers have created dedicated indexes 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.
3. Existing bottom-up approaches 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 of unlisted infrastructure investments.

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 consistently 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 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 consistently improve portfolio diversification on a total return basis.

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**EXHIBIT 1**

**Efficient Frontier January 2000 to December 2013**

<table>
<thead>
<tr>
<th>Efficient Frontier</th>
<th>Infrastructure Assets</th>
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<tbody>
<tr>
<td>Reference Portfolio</td>
<td>Hedge Fund</td>
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<tr>
<td>Real Estate</td>
<td>Immovable Property</td>
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<tr>
<td>EDRLo</td>
<td>UK Equities</td>
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<td>Western Equities</td>
<td>Oil</td>
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<td>WTEQ</td>
<td>Hedge Funds</td>
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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.

Exhibit 2 provides an illustration of these results in the case of the FTSE Macquarie Listed Infrastructure Index for the existing exposures in investors' portfolios, and that expecting 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 maximize 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 is that 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 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, i.e., 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 capitalization 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 EDHECinfra aims to answer these questions in the years to come.

### Asset class and factor-based reference

#### References


Many investors are seeking to invest today by allocating to risk factors, such as Value, Momentum, Size, Low Volatility, High Profitability and Low Investment, that are well-rewarded over the long term.

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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

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.

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