Introduction

Noël Amenc

It is my pleasure to introduce the latest issue of the Research Insights supplement to IPE, which aims to provide European institutional investors with the means to hold a customised equity portfolio that is relevant in the industry today. This supplement is an EDHEC-Risk Days Special that ties in with the flagship conference presented by EDHEC-Risk Institute in March 2016.

We compare different approaches to the design of factor indices in the equity space, notably concentrated indices and more diversified indices. We analyse broader and more narrow stock selections, as well as two different weighting schemes – equal-weighting and value-weighting. Overall, it appears that concentrated factor tilts lead to implementation challenges that are not compensated by better risk-adjusted returns. Using a more diversified weighting scheme such as equal-weighting, however, leads to significant improvements in performance with manageable implementation properties.

We then provide perspective on misconceptions about performance drivers by drawing on conceptual evidence. What we show is that, more often than not, superficially convincing claims about smart beta performance drivers stand on shaky foundations. Our analysis also shows that considering a breadth of evidence and conceptual considerations may lead to more robust conclusions and a more nuanced understanding of smart beta performance.

We sum up the results of the most recent EDHEC European ETF Survey, which was conducted at the end of 2015 with the support of Amundi ETF & Indexing. The survey shows stable high-level satisfaction with products and increasing appetite to rely on ETFs for ever more aspects of portfolio management. Moreover, we observe recent increased interest in ETFs that track smart beta indices. When it comes to smart beta ETFs, however, investment professionals also have strong quality requirements for the underlying indices, most notably in terms of transparency.

We look at whether it would make sense for a pension fund to hold a customised equity portfolio engineered to exhibit enhanced liability-hedging properties versus holding a broad off-the-shelf equity index. We conclude that investors with liability constraints will strongly benefit from switching their equity portfolio from a cap-weighted benchmark to a dedicated liability-friendly portfolio based on the selection of stocks which combine low volatility and high dividend yields and a constrained minimum-variance optimisation.

In research supported by Lyxor Asset Management, we analyse whether suitably-designed risk allocation strategies provide a cost-efficient way for investors to obtain attractive exposure to alternative factors, regardless of whether or not they can be regarded as proxies for any particular hedge fund strategy. Our results suggest that risk parity strategies applied to alternative risk factors could be a better alternative than hedge fund replication for harvesting alternative risk premia in an efficient way. We discuss the need for the investment industry to evolve towards product-based market-centred approaches and to start providing both institutions and individuals with meaningful retirement investment solutions. Well-designed retirement solutions would allow individual investors to secure the kind of performance needed to meet their consumption goals, while generating a relatively high probability for them to achieve their aspiration consumption goals. There is currently a unique opportunity for the financial industry to add value for society as a whole.

We hope that the articles in this supplement will provide useful, informative and insightful. We wish you an enjoyable read and extend our warmest thanks to IPE for their collaboration on the supplement.
Diversified or concentrated factor tilts?

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Smart beta was initially conceived as a response to two drawbacks of broad market-capitalisation-weighted (hereafter market-cap) indices. The first drawback is that such portfolios typically provide limited access to long-term rewarded risk factors such as size or value, among others. The second problem is that they do not diversify sufficiently unrewarded risks due to excessive concentration in the largest market-cap stocks. Several studies (see, eg, Choueifaty and Coignard [2008], DeMiguel et al [2009], Maillard, Roncalli and Teiletche [2010] and Amenc et al [2011] among others) have proposed methods to design indices with improved diversification as an answer to this problem. However, in recent years, the question of diversification has taken a back seat to the question of appropriate factor tilts, which has become the prime concern of smart beta providers.

Dealing with the question of obtaining the right factor exposures gives rise to a consensus because it provides space for active managers who, in a framework of smart beta offerings purely focused on improving diversification, had little space. Factor investing has become an opportunity to sell stock-picking approaches as systematic strategies. The vast majority of index providers focus only on identifying the right factor exposures and maximising them. In doing so, they create indices that are heavily concentrated in a few stocks. Indeed, over the long term, the idea behind such offerings is to maximise the return associated with the strongest exposure possible to the rewarded risk factor. Providers thus frequently emphasise that obtaining strong factor exposure is a prime objective of their indices.

In this article we discuss the conceptual implications of concentration arising from such approaches and contrast concentrated approaches with more diversified ones. We also report on an empirical comparison of the performance of concentrated and diversified factor-tilted portfolios on broad and narrow factor-filtered stock universes using long-term US stock data. We draw on results from Amenc et al (2016), who have provided a comprehensive assessment of concentrated versus diversified factor tilts.

The need for diversification within factor-tilted portfolios

Positive exposure to rewarded factors is obviously a strong and useful contributor to expected returns. However, products that aim to capture explicit risk-factor tilts often neglect adequate diversification. This is a serious issue because diversification has been described as the only ‘free lunch’ in finance. It allows a given exposure to be captured with the lowest level of risk required. In contrast, gaining factor exposures exposes investors to additional types of risk, and therefore, such exposures do not constitute a ‘free lunch’. They instead constitute compensation for risk in the form of systematic factor exposure. Such capturing of risk premia associated with systematic factors is attractive for investors who can accept the systematic risk exposure in return for commensurate compensation.

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

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

Moreover, this extreme case of a strong factor tilt indicates what the potential issues with highly concentrated factor indices are. First, such an extreme strategy will allow the highest possible amount of return to be captured from the value premium, but it will necessarily come with a large amount of idiosyncratic risk, which is not rewarded and therefore should not be expected to lead to an attractive risk-adjusted return. Second, it is not likely that the same stock will persistently have the highest value exposure within a given investment universe. Therefore, a periodically rebalanced factor index with such an extreme level of concentration is likely to generate 100% one-way turnover at each rebalancing date, as the stock held previously in the strategy is replaced with a new stock that displays the highest current value exposure. While practical implementations of concentrated factor-tilted indices will be less extreme than this example, we can expect problems with high levels of idiosyncratic risk and high levels of turnover whenever index construction focuses too much on concentration and pays too little attention to diversification.

Interestingly, the importance of diversification for a given factor tilt was outlined several decades ago in one of Benjamin Graham’s famous books on value investing: “In the investor’s list of common stocks there are bound to be some that prove disappointing... For example, the standard Fama and French value factor includes a broad selection of stocks, and uses a two-tiered weighting approach to obtain better diversification. In particular, the value factor is an equal-weighted combination of sub-portfolios for different market cap ranges, effectively overweighting smaller size stocks and increasing the effective number of stocks. The fact that the most widely-cited research documenting the relevance of the value factor does not use simple cap-weighted factors, but rather constructs more balanced portfolios, shows the lack of support for industry practices using simple cap-weighted factor indices.

Furthermore, Asparouhova, Bessembinder and Kalcheva (2013) review the literature and summarise that “examining papers published in only two premier outlets, the Journal of Finance and the Journal of Financial Economics, over a recent 5-year (2005 to 2009) interval, we are able to identify 24 papers that report EW mean returns and compare them across portfolios” (see also Uppal, Plyakha and Vilkov [2014]). As a recent example, Hou, Xue and Zhang (2015) address the diversification issue by forming...
factor portfolios which equal-weight their component stocks, while excluding the smallest stocks due to implementation concerns. Overall, it thus appears that the approach that proposes to construct concentrated factor indices is supported neither by the academic literature, nor for that matter, by common sense. On the contrary, there is a strong theoretical motivation for constructing well diversified factor tilted portfolios.

Performance of concentrated versus diversified tilted portfolios

Data and methodology

In this section, we compare portfolios for six factor tilts, each with different stock selection filters, which are constructed using two different weightings – cap weighting (CW) and equal weighting (EW). Two kinds of filtering are used: the broad filtering selects the top 50% stocks, in terms of factor scores, from the stock universe at each rebalancing and the narrow filtering selects the top 20% stocks. The idea behind this 20% filter is of course to test the commonly accepted idea that the more the portfolio is concentrated in stocks that are most exposed to a factor that is well rewarded over the long term, the better the portfolio will perform.

All stocks are assigned factor scores that are determined by their fundamental stock characteristics or past returns. Each stock is assigned six factor scores. To construct factor-tilted portfolios, the top 50% or top 20% stocks are selected at each annual rebalancing by their factor scores. This means that approximately 250 and 100 stocks are selected from the broad universe of 500 US large-capitalisation stocks. The factor-tilted cap-weighted portfolio weights the selected stocks in proportion to their total market capitalisation. The equal-weighted portfolio weights the selected stocks in equal proportion.

All tilted portfolios are rebalanced annually on the third Friday of June except the momentum-tilted portfolios, which are rebalanced semi-annually. The analytics on US portfolios in subsequent sections use 40 years of weekly total returns – i.e., returns with dividends reinvested. Stock-level data for portfolio construction and portfolio valuation is obtained from CRISP and WRDS. The long/short factor returns used for regression are obtained from Kenneth French's data library.2

Performance comparison of concentrated and diversified factor-tilted portfolios

Diversification leads to superior performance

Figure 1 shows a detailed comparison between well diversified (EW) portfolios and heavily-concentrated (CW) portfolios and Figure 1 shows a detailed comparison between Kenneth French's data library.

2 The following factor scores are used for each of these six factor tilts – mid cap: total market cap stocks; value: book-to-market (B/M) ratio. B/M is defined as the ratio of available book value of shareholders’ equity to company market cap; high momentum: total returns over the past 52 weeks, minus the last four weeks; low volatility: standard deviation of weekly stock returns in the past 104 weeks; low investment: past two-year total asset growth rate; high profitability: gross profit-to-total asset ratio. The factor scores for mid cap, low volatility and low investment factors are inverted.

3 Weekly returns on S&P, HML and UMD long/short factors in the US can be obtained from the following web link: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

1. Performance of cap-weighted and equal-weighted factor indices

<table>
<thead>
<tr>
<th>Broad</th>
<th>Top 50% stocks selected by factor score</th>
<th>Top 20% stocks selected by factor score</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CW</td>
<td>EW</td>
</tr>
<tr>
<td>Annualised returns</td>
<td>12.26%</td>
<td>13.87%</td>
</tr>
<tr>
<td>Annualised volatility</td>
<td>16.09%</td>
<td>16.04%</td>
</tr>
<tr>
<td>Sharpe ratio</td>
<td>0.44</td>
<td>0.55</td>
</tr>
<tr>
<td>Annualised relative returns</td>
<td>1.65%</td>
<td>2.75%</td>
</tr>
<tr>
<td>Annualised tracking error</td>
<td>1.60%</td>
<td>5.74%</td>
</tr>
<tr>
<td>Information ratio</td>
<td>0.33</td>
<td>0.66</td>
</tr>
<tr>
<td>Outperformance probability (3Y)</td>
<td>68.12%</td>
<td>76.04%</td>
</tr>
</tbody>
</table>

1. Average relative return – 3.22% 5.60% 5.33% 7.05% 1.32% 2.86%

2. Relative return – 2.35% 3.92% 3.56% 3.89%

3. Annualised standard deviation – 4.61% 5.74% 7.53% 7.79% 4.82% 5.67%

These results confirm that, contrary to widespread opinion, well diversified factor portfolios outperform their heavily concentrated counterparts in terms of risk-adjusted performance, not because they are exposed to other systematic risk factors (like mid-cap risk for example), but because the concentrated factors are highly exposed to unrewarded factors.
Concentration leads to severe implementation costs

A frequent criticism of EW as a weighting scheme is that EW portfolios overweight small-cap stocks, thus posing implementation challenges, since small-cap stocks are relatively less liquid. Figure 3 shows that switching from a 50% CW factor-tilted portfolio to an EW factor-tilted portfolio reduces DTT by 2.41 to 2.35 days, which is a considerable decrease in time required to sell stocks. Therefore, the weighting scheme does not contribute much additional turnover.

Due to their nature of strongly underweighting smaller stocks, cap-weighted portfolios exhibit low daily turnover (DTT) numbers. DTT is an indicator of the time required to sell the largest liquid positions in the portfolio. DTT increases when moving from CW to EW, but remains well behaved. It should be noted that one can use additional liquidity management rules to improve the turnover and DTT of an equal-weighting strategy or other alternative weighting schemes (Amenc et al, 2014 and Gonzalez et al, 2015).

Conclusion

This article, drawing on Amenc et al (2016), compares different approaches to factor index design, notably concentrated indices and more diversified indices. We analyse broader stock selections and more narrow stock selections, and two different weighting schemes, equal-weighting and cap-weighting.

From a conceptual perspective, several issues arise with highly concentrated portfolios such as cap-weighted portfolios of narrow stock selections. First, concentration in few stocks reflects high confidence in the precision of the link between expected returns and factor exposure. However, we know that expected returns are notoriously difficult to estimate with precision, even when doing this through factor exposures. Broadly-diversified factor-tilted portfolios reflect the view that we are only able to identify broad differences in expected returns across stocks. By including many stocks, it will be more likely that factor premia can be identified reliably only for broadly-diversified tilted portfolios. Empirical studies of factor premia insist on the necessity of constructing broad portfolios that are not unduly influenced by a small number of large-cap stocks, which has led the major studies in this area to adopt approaches that lead to diversified portfolios, notably by selecting large numbers of stocks and by using more balanced weighting approaches than simple cap-weighting for the selected stocks.

Our empirical analysis confirms that concentrated factor-tilted portfolios come with problems. In fact, trying to improve the performance of CW factor-tilted portfolios by selecting fewer stocks that are most strongly tilted towards the factor does not have any positive effect on the risk-adjusted performance. Narrow stock selections improve returns compared to broad selections, but this increase is accompanied by higher volatility and higher tracking error, which keeps performance ratios – the Sharpe ratio and information ratio – unchanged. In addition, factor-tilted portfolios on narrow stock selections present other drawbacks such as high idiosyncratic risk, higher turnover and longer times to trade portfolios. Conversely, if one focuses on deconcentration by using a simple EW to weight stocks, better Sharpe ratios and information ratios can be achieved over both long and short investment horizons. The EW portfolios incur only marginally higher (but manageable) levels of turnover and in total do not pose implementation problems. These observations stand true across the six risk factors tested.

Overall, it appears that concentrated factor tilts lead to implementation challenges that are not compensated by better risk-adjusted returns. Using a more diversified weighting scheme such as equal-weighting, however, leads to significant improvements in performance with manageable implementation properties. Equal-weighting can be seen as a starting point for more sophisticated diversification strategies, such as risk-based diversification strategies, which may allow for additional benefits to be obtained as proposed by Amenc et al (2014) within the framework of implementing diversification based on a multi-strategy approach to factor indices.

References

Amenc, N., F. Goltz and N. Gonzalez (2014). Risk-Based Dynamic Portfolio Management. SSRN.
Common misconceptions about smart beta performance drivers

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Smart beta strategies have been one of the strongest growth areas in investment management over the past decade. Such strategies have also drawn fierce criticism from providers of both traditional active management and index providers. Smart beta providers are not only responding to such criticism, but have been vocal about the benefits of their respective approaches, without necessarily agreeing with each other. Such debates have the potential to clarify the issues at hand by discussing the facts. Unfortunately, however, by often recurring to superficially convincing arguments that may not align well with the facts, such debates have also led to a number of misconceptions. Misconceptions about smart beta have arisen in different areas, such as performance drivers, investability issues and strategy design choices. Amenc et al. (2016) address 10 common claims about smart beta and reveal the underlying misconceptions. In this article, we provide a summary of their results concerning a specific area, namely the sources of outperformance of smart beta strategies.

Misconception 1: ‘Smart beta generates alpha’

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

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

Beyond implementing a simple tilt to a rewarded risk factor, smart beta strategies may use two different approaches to improve risk-adjusted investment outcomes without being related to a single factor. One of these is the systematic nature of well-diversified factor indices, which is widely known and can be implemented in a mechanistic framework. In this sense, such returns are neither ‘unexplained’ nor attributable to any form of skill. Beyond implementing a simple tilt to a rewarded risk factor, smart beta strategies may use two different approaches to improve risk-adjusted investment outcomes without being related to a single factor. One of these is the systematic nature of well-diversified factor indices, which is widely known and can be implemented in a mechanistic framework. In this sense, such returns are neither ‘unexplained’ nor attributable to any form of skill.

First, smart beta strategies may aim to provide better diversification for a given factor tilt. Indeed, it is consistent with asset pricing models that expected returns depend linearly on the exposure to a given risk factor. Thus, one could simply aim to maximise exposure to this factor by concentrating a portfolio in a few stocks or – if taken to the limit – in a single stock with the highest factor exposure. However, such an approach will inevitably take on unrewarded risk, notably stock-specific risk, thus leading to inferior risk-adjusted returns. Smart beta strategies may combine the benefits of tilting to rewarded factors with the benefits of constructing well-diversified portfolios. For example, Amenc et al. (2016) provide evidence that well-diversified factor-tilted portfolios lead to improved risk/return properties relative to concentrated portfolios tilting to the same factor. Such an approach of building well-diversified factor indices thus delivers improved risk-adjusted returns by avoiding taking on unrewarded risk. Such well-diversified factor-tilted portfolios consider not only the evidence from asset pricing on additional risk factors, but also take into account the insights from portfolio theory (Markowitz [1952]), namely that diversification allows part of the risk to be cancelled. The key idea of well-diversified factor-tilted indices is to access the reward associated with exposure to systematic factors while diversifying away unrewarded risk (see Amenc et al. [2010]). Such an approach cannot be equated with manager skill or superior information and in this sense does not constitute alpha.

Second, smart beta strategies may add value through factor risk allocation. Indeed, strategies that tilt to a single factor – even if they are well diversified in the sense of avoiding exposure to unrewarded risk – are somewhat limited since they ignore the potential benefits of allocating to several factors. Factor allocation approaches combine exposures to several rewarded factors. By exploiting the information on risk parameters, and notably the correlation structure across factors, such factor allocation approaches allow risk-tilted beta strategies to be implemented in a mechanistic framework. In this sense, such returns are neither ‘unexplained’ nor attributable to any form of skill. Factor allocation approaches consider information on risk parameters and investor objectives but do not aim to predict the future realisation of returns. Such approaches are not related to manager skill or alpha since they draw on allocation techniques which are entirely systematic and focus on using information on risk parameters without estimating future returns at all without the need to forecast future returns.

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

In fact, smart beta strategies resemble traditional cap-weighted beta strategies in many aspects, such as high levels of transparency, relying on well-documented factors and weighting methodologies, and low fees. This resemblance is essentially due to the fact that smart beta strategies can be entirely systematic, just as cap-weighting is. As outlined above, this systematic nature nevertheless offers three distinct sources of added value, namely (i) access to additional rewarded factors beyond the market factor, (ii) improved diversification targeted at avoiding exposures to unrewarded risks, and

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§ (iii) factor risk allocation allowing information on the risk parameters of a set of factors to be exploited to construct portfolios that correspond to targeted risk objectives. These sources of added value are not alpha in the sense that they do not correspond to any capacity to generate abnormal returns by predicting future asset or factor returns beyond information that is available from market prices.

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

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

**Misconception 2: Anything beats cap-weighted market indices**

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

Here we summarise results from Amenc et al (2015), who empirically assess the validity of such claims for a range of test portfolios. Figure 1 provides an extract of some of the results, where the authors invert simple factor-tilted strategies which employ stock selection and score-based weighting to obtain a given factor tilt. Such strategies are closely related to common offerings in the area of smart beta indices. The figure provides performance statistics relative to the cap-weighted reference index for both the original strategies and the inverted strategies. The table below shows that inverting the strategy does not only turn the weights upside-down, but also changes the performance. For example, while a value-tilted strategy leads to a positive outperformance of 3.9% annualised, the inverse of this strategy leads to –2.07% returns relative to the cap-weighted reference index. Similar results hold for all other factor tilts. These results suggest that, rather than being irrelevant, the investment beliefs in the form of explicit factor tilts do indeed play an important role in determining the performance of an investment strategy.

<table>
<thead>
<tr>
<th>Stock selection</th>
<th>Weighting scheme</th>
<th>Annualised returns</th>
<th>Information ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mid-cap</td>
<td>Upside-down</td>
<td>4.48%</td>
<td>0.600</td>
</tr>
<tr>
<td>Large cap</td>
<td>Upside-down</td>
<td>–1.04%</td>
<td>–0.38</td>
</tr>
<tr>
<td>High momentum</td>
<td>Momentum score weighted</td>
<td>1.96%</td>
<td>0.34</td>
</tr>
<tr>
<td>Low momentum</td>
<td>Upside-down</td>
<td>–2.85%</td>
<td>–0.32</td>
</tr>
<tr>
<td>Low volatility</td>
<td>Low volatility score weighted</td>
<td>0.54%</td>
<td>0.09</td>
</tr>
<tr>
<td>High volatility</td>
<td>Upside-down</td>
<td>–1.89%</td>
<td>–0.6</td>
</tr>
<tr>
<td>Value</td>
<td>Value score weighted</td>
<td>3.94%</td>
<td>0.66</td>
</tr>
<tr>
<td>Growth</td>
<td>Upside-down</td>
<td>–2.07%</td>
<td>–0.51</td>
</tr>
<tr>
<td>Low investment</td>
<td>Low investment score weighted</td>
<td>2.31%</td>
<td>0.52</td>
</tr>
<tr>
<td>High investment</td>
<td>Upside-down</td>
<td>–1.80%</td>
<td>–0.38</td>
</tr>
<tr>
<td>High profitability</td>
<td>High profitability score weighted</td>
<td>0.85%</td>
<td>0.15</td>
</tr>
<tr>
<td>Low profitability</td>
<td>Upside-down</td>
<td>–0.58%</td>
<td>–0.08</td>
</tr>
</tbody>
</table>

All statistics are annualised and daily total returns from 31 December 1997 to 31 December 2012 are used for the analysis. The CRSP S&P 500 index is used as the cap-weight benchmark. The table reproduces results for a selection of ‘Type 1’ upside-down strategies from exhibit 6 in Amenc et al (2015).

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

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

Some argue that once we deviate from selecting and weighting stocks by their market value, as is done in cap-weighted market indices, this “necessarily results in value and size tilts, regardless of the weighting method chosen”. These tilts suffice to explain outperformance. While this may obviously be true for some smart beta strategies which – by design – will lead only to small-cap and value exposures, this notion is inconsistent with evidence on a wide range of smart beta strategies. In particular, Amenc, Goltz and Lodh (2015) show that typical factor-tilted smart beta strategies can have exposure to factors other than small-cap and value. This finding may not be surprising, and is fully consistent with the academic literature, which has documented the importance of various equity risk factors beyond value and small cap (Leote de Carvalho, Lu and Moulin (2012); Clarke, de Silva and Thorley (2013); Amenc, Moskowitz and Pedersen (2013); Amenc, Frazzini and Pedersen (2013)).

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

Moreover, they show that many smart beta strategies present a considerable portion of unexplained performance, which suggests that the portfolio construction of these indices captures effects that cannot be explained fully.

11 Cited above.
16 Cited above.
by the relevant factors. Possible explanations of this unexplained part of performance are that the improved diversification scheme allows for the rebalancing effect, or that there is another factor that is not captured explicitly. However, this finding is consistent with the notion that different smart beta strategies derive performance from different exposures to several factors that may go beyond size and value.

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

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

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

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

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

On the first matter, empirical research has shown that rebalancing effects are highly dependent on the time horizon. There is ample evidence not only of return reversal effects, but also of return continuation momentum effects (Jegadeesh and Titman [1995]). More recently, Fylikha, Upal and Vilko (2012)show that rebalancing effects only occur at a frequency which is much higher than typical index rebalancing frequencies. A recent paper by Cuthbertson et al (2015)recognises that there is no consensus in the literature on the existence of a positive rebalancing effect. Qian (2014)provides an analysis suggesting that whether a rebalanced portfolio will outperform a buy-and-hold portfolio or underperform is dependent on the rebalancing frequency. Given this dependency of a rebalancing bonus on specific conditions, it is perhaps not surprising that that standard asset pricing models such as those of Fama and French (1993), (2015) and Carhart (1997)do not include any rebalancing factor.

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

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

---

**2. Performance evaluation (alpha measurement) in a model with reversal factors**

<table>
<thead>
<tr>
<th>SciBeta Long-Term USA Maximum Mid-cap Maximum Deconcentration</th>
<th>SciBeta USA High Momentum Maximum</th>
<th>SciBeta Long-Term USA Mid-cap Maximum Deconcentration</th>
<th>SciBeta Long-Term USA Mid-cap Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Annualised relative returns</td>
<td>2.56%</td>
<td>3.64%</td>
<td>4.52%</td>
</tr>
<tr>
<td>Regression on market factor and reversal factors</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Annualised alpha</td>
<td>1.85%</td>
<td>2.68%</td>
<td>3.42%</td>
</tr>
<tr>
<td>Market reversal factor</td>
<td>0.98</td>
<td>0.97</td>
<td>0.97</td>
</tr>
<tr>
<td>Short-term reversal factor</td>
<td>0.01</td>
<td>0.02</td>
<td>0.00</td>
</tr>
<tr>
<td>Long-term reversal factor</td>
<td>0.15</td>
<td>0.09</td>
<td>0.28</td>
</tr>
<tr>
<td>R-squared</td>
<td>94.71%</td>
<td>93.51%</td>
<td>90.22%</td>
</tr>
</tbody>
</table>

The results are based on daily total returns during the period from 31 December 1974 to 31 December 2014. The market factor is the excess returns of the CRSP S&P 500 index over the risk-free rate. The standard US Treasury bill rate is used as a proxy for the risk-free rate. The reversal factors are obtained from Kenneth French’s data library. Statistics are annualised. Regression coefficients significant at the 95% level are highlighted in bold.
Since November 23, 2009, EDHEC-Risk Institute has been designing equity smart beta indices.

With live annualised outperformance of 2.41%¹ for more than six years, these Smart Beta 1.0 indices based on the Efficient Maximum Sharpe Ratio methodology have shown that a good diversification method can lead to significant and robust outperformance over cap-weighted indices.

Since 2012, with the Smart Beta 2.0 framework, EDHEC-Risk Institute has created Scientific Beta Smart Factor Indices that are even better diversified and therefore more successful.

The Scientific Beta Smart Factor Indices for the rewarded long-term risk premia of Mid-Cap, Value, Momentum and Low Volatility have all produced positive annualised performance for all regions since they went live on December 21, 2012, with average annualised outperformance over the cap-weighted benchmark of 2.90%².

The Scientific Beta multi-smart-factor indices, which allocate to these four Smart Factor Indices, have a live track record that is even better than that of our Smart Beta 1.0 offering, with an annualised outperformance of 4.00% compared to their cap-weighted benchmark.³

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

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

¹ - The average annualised outperformance of the FTSE EDHEC-Risk Efficient Index series (all regions) is 2.41% compared to its cap-weighted benchmark, computed using daily total returns from November 23, 2009 (live date) to December 31, 2015. The regions in question are the USA, UK, Eurobloc, Japan, Developed Asia-Pacific ex Japan and Developed World. The benchmark used is a cap-weighted portfolio of all stocks in the respective Scientific Beta universes.

² - Analysis is based on daily total returns from December 21, 2012 to December 31, 2015 for the USA, Eurozone, UK, Developed Europe ex UK, Japan, Developed Asia Pacific ex Japan, Developed ex UK, Developed ex US and Developed regions. The live date of the four Smart Factor Indices – Mid-Cap, Value, Momentum and Low Volatility – is December 21, 2012 for all regions. The benchmark used is a cap-weighted portfolio of all stocks in the respective Scientific Beta universes. The average outperformance for each factor across all regions is as follows: Mid-Cap (2.62%), Value (1.15%), Momentum (4.31%) and Low Volatility (3.50%), leading to an average across all four factors of 2.90%. All statistics are annualised. Source: scientificbeta.com.

³ - The average live outperformance across all Scientific Beta developed regions of Scientific Beta Multi-Beta Multi-Strategy (Equal Weight and Relative Equal Risk Contribution) indices is 4.00% and 3.77% respectively, while that of the Efficient Maximum Sharpe Ratio strategy in the same period is 2.85%. This live analysis is based on daily total returns in the period from December 20, 2013 (live date) to December 31, 2015, for the following developed world regions – USA, Eurozone, UK, Developed Europe ex UK, Japan, Developed Asia Pacific ex Japan, Developed ex UK, Developed ex USA and Developed. The benchmark used is a cap-weighted portfolio of all stocks in the respective Scientific Beta universes.

Information containing any historical information, data or analysis should not be taken as an indication or guarantee of any future performance, analysis, forecast or prediction. Past performance does not guarantee future results.
such strategies. This result suggests that the performance of these strategies is not primarily driven by the reversal factors and the associated rebalancing effects.

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

Towards a differentiated understanding of performance drivers

That the growth of smart beta is accompanied by intense debate is not surprising. Such debate should have the merit of furthering the understanding of potential benefits, as well as risks, in the area of smart beta investing, intense debate has, however, also produced a certain number of conclusions that are seen as common wisdom, despite not always necessarily being in line with the facts.

The objective of this article is to provide a perspective on misconceptions about performance drivers by pointing out conceptual considerations and empirical evidence. The analysis in this article shows that, more often than not, superficially convincing claims about smart beta performance drivers stand on shaky foundations. Our analysis also shows that taking into account a breadth of evidence and conceptual considerations may perhaps lead to more balanced conclusions and a more nuanced understanding of smart beta performance. Our analysis does not aim to provide a conclusion on the universal properties of all smart beta strategies. In fact, all too often, claims about performance drivers of smart beta abstract from the large variety of approaches that exist. Accounting for the differences across different strategies is necessary to avoid rushing to premature conclusions. Indeed, many of the misconceptions correspond to over-generalisations that do not sufficiently take into account that the term ‘smart beta’ captures a vast variety of strategies with potentially very different properties. For example, it may be correct for some smart beta strategies to say that they are solely driven by value and small-cap tilts or that they yield similar results when one inverts the strategy. However, this does not mean that such conclusions apply to all smart beta strategies. In a nutshell, our analysis cautions against over-simplification and calls for a detailed analysis of smart beta strategy performance taking into account the specific properties of the respective strategy.

References


Fresh evidence from the EDHEC European ETF Survey 2015

Felix Goltz, Head of Applied Research, EDHEC-Risk Institute, Research Director, ERI Scientific Beta; Véronique Le Sourd, Senior Research Engineer, EDHEC-Risk Institute

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DHEC-Risk Institute conducted its ninth survey of European investment professionals on the usage and perceptions of ETFs at the end of 2015. EDHEC-Risk Institute’s ETF surveys now provide a continuous assessment of practices and views among professional investors since 2006. Responses provide interesting insights into the trends and developments in the ETFs industry, in line with the confirmation of a long-term trend established in our past surveys, which shows a stable and high level of satisfaction with products, as well as an increasing appetite to rely on ETFs for ever more aspects of portfolio management. Moreover, we observe a recent increase in interest for ETFs that track smart beta indices.

When it comes to smart beta ETFs, investment professionals, however, also have strong quality requirements for the underlying indices, most notably in terms of transparency.

Our results are based on the responses of 219 European investment decision-makers, of which 180 use ETFs. The survey respondents were from 25 countries, with more than half (52%) located in the UK, Switzerland or Italy. Institutional investment managers made up the majority of respondents in the study, with 76%, and participating organisations together have assets under management of at least €3.1tn.

In the present article, we sum up the main results of the survey. We first turn to key results concerning perceptions about ETFs in general and then address results relating to the perceptions on smart beta ETFs in particular.

ETFs are seen as high-quality instruments

Satisfaction with standard ETFs has generally remained at high levels for traditional asset classes, as shown in figure 1. Compared to 2014, there has been an increase in satisfaction with equity ETFs, with more than 9% of users indicating satisfaction rate of 96%, compared to 91% in 2014. The stable and high rate of equity ETF satisfaction, which has consistently been in the region of 90% since
Prospects of further increases in the use of ETFs

Another interesting result from our survey is that respondents plan to further increase their use of ETFs (see figure 2). We note that the percentage of respondents who plan to increase ETF usage is stable over time, at around 60% since 2011. Moreover, this interest in increasing ETF usage can be contrasted with the lower percentage of investors who plan to increase their use of other indexing instruments such as futures (31%), index funds (21%), or total return swaps (TRS – 12%). It thus appears that ETFs not only benefit from increasing interest in index investments, but also that ETF investors have a more favourable outlook of their use than the use of alternative indexing products.

In view of these results, it is interesting to investigate investors’ motivations for increasing their use of ETFs. As seen in figure 3, increases in ETF allocation are motivated primarily by cost considerations for the vast majority of respondents (80%), followed by performance (50%), transparency (46%) and then liquidity (43%). A comparison with the 2014 results shows an increase in all criteria. We also find evidence that ETFs are seen more frequently as a substitute for active management rather than a substitute for other indexing vehicles. 74% of respondents (versus 64% in 2014) declare that increasing the use of ETFs will serve as a substitute to the use of active managers, while 64% (versus 42% in 2014) of them will substitute them for other indexing products.

These results can be linked to the disappointing performance of active management, as illustrated by academic papers showing that few active funds are able to produce returns high enough to compensate management fees (see Barra, Scaillet and Wermers [2010] and Fama and French [2010]). In this context, investors may see the use of ETFs as more profitable and less costly than the use of active managers. ETFs allow investors to mimic the performance of all types of asset classes, including various smart beta products, while limiting costs. This trend among investors can be seen as a response to the increase in fees in the investment management industry described by Malkiel (2013). Investors dedicate more resources to evaluating active management than indexing or smart beta products.

Our survey also allowed us to assess which resources are employed by investors to evaluate products in the two main investment management approaches, active and passive, and in smart beta strategies, which are seen as a third way between the two extremes. While
respondents spent a comparable percentage of their time evaluating passive management and active managers (21% and 23% respectively), they only spent 15% of their time evaluating smart beta and systematic factor investments (see figure 4).

Differences are even greater with regard to the percentage of full-time staff involved in evaluating the different forms of investment. While 25% of full-time staff are dedicated to the evaluation of active managers, only 17% of full-time staff are employed for the evaluation of cap-weighted indices and passive investment products, and only 10% for the evaluation of smart beta or systematic factor investments. It is striking that the highest resource allocation is given to the evaluation of active managers. Moreover, a striking gap exists between the

“A striking gap exists between the resources allocated to smart beta evaluation and the resources allocated to evaluating either traditional active management or traditional passive management products. Resources allocated to smart beta product evaluation clearly lag behind.”

resources allocated to smart beta evaluation and the resources allocated to evaluating either traditional active management or traditional passive management products. Resources allocated to smart beta product evaluation clearly lag behind. With the increasing popularity of smart beta products, more resources should be devoted to evaluating the various offers. However, our results suggest that investors do not necessarily have adequate resources for smart beta, which is a more recent phenomenon that constitutes a new category in between traditional passive and active management.

Perceptions of smart beta ETFs

For the third year, our survey includes information on respondents’ use of products tracking smart beta indices. It appears from the results that investors continue to show high and increasing interest in smart beta ETFs. More than a third of respondents (37%) already use products tracking smart beta indices, compared to 25% in 2014, and another third (33%) do not currently invest in such products but are considering investing in them in the near future (see figure 5). These results imply that we are likely to see strong growth in the usage of smart beta ETFs in the future.

In addition, ETFs based on smart beta indices top respondents’ concerns with regard to developments in the future, with 38% of them hoping for further developments in this area. This broad use of ETFs based on smart beta indices, as well as the wishes for additional development, may be explained by the favourable perception that respondents have of smart beta indices as tools for improving their investment process, as shown by their answers to further questions.

As displayed in figure 6, three-quarters of respondents (79%) think that smart beta indices allow factor risk premia, such as value and small-cap, to be captured. Thus, there is strong agreement from respondents with the conclusions from research on the potential benefits of smart beta.

In addition to showing strong interest in smart beta ETFs, survey respondents have strong quality requirements for such products. A notable requirement is transparency. A vast majority of respondents (94%) agree that smart beta indices require full transparency on methodology and risk analytics (see figure 7), a percentage even higher than the 88% obtained in

4. Resources employed for evaluation of investment strategies and products within your organisation

<table>
<thead>
<tr>
<th>Evaluation of cap-weighted indices and passive investment products</th>
<th>Evaluation of active managers</th>
<th>Evaluation of smart beta or systematic factor investments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percentage of time (%)</td>
<td>Percentage of full-time staff %</td>
<td></td>
</tr>
</tbody>
</table>

This figure indicates the average percentage of time personally spent by respondents on evaluating passive investment, active managers and smart beta or systematic factor investments, respectively, as well as the percentage of full-time staff personally involved in the evaluation of passive investment, active managers and smart beta or systematic factor investments, respectively.

5. Use of products tracking smart beta indices

<table>
<thead>
<tr>
<th>My organisation is investing in such products</th>
<th>My organisation is considering investing in such products in the near future</th>
<th>My organisation is not investing and not considering investing in such products in the near future</th>
</tr>
</thead>
<tbody>
<tr>
<td>2015 (%)</td>
<td>2014 (%)</td>
<td>2015 (%)</td>
</tr>
</tbody>
</table>

This figure indicates the percentages of respondents that reported using products tracking smart beta indices, as well as the percentage of respondents that plan to use them in the future. Non-responses are excluded.

6. Agreement of respondents with statements about smart beta indices

<table>
<thead>
<tr>
<th>Diversification across several weighting methodologies allows risk to be reduced and adds value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Smart beta indices allow the concentration of cap-weighted indices in very few stocks or sectors to be avoided</td>
</tr>
<tr>
<td>Smart beta indices allow factor risk premia such as value and small cap to be captured</td>
</tr>
<tr>
<td>Smart beta indices provide sufficient potential to outperform cap-weighted indices in the long term</td>
</tr>
</tbody>
</table>

This figure indicates the percentage of respondents that agree or strongly agree with the statement about smart beta indices. Non-responses are excluded.
Information requirements for smart beta (importance vs accessibility)

Transparency is a general requirement that may concern different types of information items. Our survey investigates which types of information on smart beta strategies are seen as most important by investors, and which items are seen as easy or difficult to access. Among a list of ten items proposed, we can see that all of them received a high score in terms of importance. On a scale from 0 (lowest importance) to 5 (highest importance), the lowest score observed is around 3, and a large share of propositions receive a score around 4 (see figure 8). At the top of the list of information considered as crucial by investors, we find all information concerning the construction, composition, strategy and exposure to factors of smart beta products, while at the bottom of the list is information regarding historical performance.

At the same time, respondents were asked whether they considered this information easily available. Thus, it is interesting to see the spread between the importance of the information and the accessibility to this information. Information about portfolio holdings over the back-test period and about data mining risk are crucial pieces of information for respondents, with scores of 4.03 and 3.81, respectively. It is also the information that appears to be the most difficult to obtain for respondents, with scores of 2.16 and 2.07, respectively, leading to a large gap between importance and availability of information. Even relatively basic information such as the index construction methodology is not judged to be easily available (score of 3.07).

The gap between information importance and its accessibility, as seen by investors, is displayed in figure 9. A high spread reflects a shortfall of providers when they do not give easy access to crucial information.

The fact that information is regarded as important is not considered to be easily avail-
able clearly calls into question the information provision practices of smart beta providers. In fact, the only area where no pronounced gap exists between the importance and the ease of accessibility score is for performance numbers, especially recent performance. Performance and risk information are judged to be moderately easily available and moderately important. Other areas show pronounced gaps between the importance of provision and its ease of availability. The two items that are judged to be the least easily available are holdings over the backtest period and datamining risks. Interestingly, both these items rank much higher on the importance score for performance than, for example, past performance. Moreover, there is a pronounced gap between the importance of information items and their ease of accessibility, as shown by the mean of their respective scores (3.82 and 2.75, respectively), showing a gap of 1.07, on average. Overall, these results suggest that investors do not believe that information considered important for assessing smart beta strategies is made available to them with sufficient ease.

Conclusions
Our survey of a broad cross-section of ETF users provides interesting insights into recent trends. Concerning general ETF investing, respondents show positive appreciation of ETFs as low-cost indexing instruments, with a positive outlook on future usage. Concerning smart beta ETFs, respondents show pronounced interest in such instruments overall and strongly appreciate potential benefits. However, it also emerges from our survey that investors face several challenges when evaluating such products, most notably because of lack of resources allocated to smart beta assessment and a lack of easy access to information. Going forward, it will be interesting to follow the future developments in this area to see how practices and perceptions evolve.

The research from which this article was drawn was produced as part of the Amundi ETF & Indexing ETFs and Passive Investment Strategies research chair at EDHEC-Risk Institute.

References

Liability-driven investing and beyond: fund separation versus the theorems
Asset-liability management (ALM) for pension funds has become relatively straightforward, in principle, within the paradigm known as liability-driven investing (LDI). In a nutshell, when extended to ALM, modern portfolio theory and the fund separation theorem unambiguously advocate that pension plans should implement the suitable combination of a liability-hedging portfolio (LHP) invested in fixed-income securities and aiming to match the risk factors impacting the value of their liabilities as well as possible, and a performance-seeking portfolio (PSP) aiming to efficiently harvest risk premia across and within risky asset classes, and most importantly in equity markets around the globe. When a pension fund is underfunded, pension assets are by definition insufficient to cover the liabilities, but the pension fund may in principle acquire additional resources allocated to make up for the gap between pension assets and pension liabilities and also maintain a levered investment in performance-seeking assets which may contribute to solving the funding problem without requiring exceedingly high levels of additional contributions.

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

In this context, the question arises of whether it would make sense for a pension fund to hold a customised equity portfolio engineered to exhibit enhanced liability-hedging properties versus holding a broad off-the-shelf equity index. Intuition indeed suggests that a better alignment of the PSP with respect to the liabilities would lead to an increased allocation to stocks for the same level of volatility of the funding ratio, which in turn would provide superior access to the equity risk premium. This article extends the LDI paradigm by assessing whether LDI solutions can be enhanced by the design of performance-seeking equity benchmarks with improved liability-hedging properties. We confirm this intuition and show that improving the hedging characteristics of the performance portfolio generates welfare gains unless this improvement comes at an exceedingly large opportunity cost in terms of performance, a result that we call the fund interaction theorem. While two competing effects exist in principle (a better alignment of the equity portfolio with the liabilities leads to a higher allocation to equities for the same ALM risk budget due to enhanced liability-friendliness, but it may also lead to a lower reward per dollar invested compared to a pure focus on performance), our empirical analysis actually suggests that the selection of stocks with above-average liability-hedging properties leads to both a higher degree of liability-friendliness (as expected) and also to better performance due to increased exposure to rewarded factor tilts.

In this context, we find that very substantial increases in investor welfare would come from switching from a standard off-the-shelf cap-weighted (CW) equity benchmark to an equity benchmark designed to exhibit liability-driven investing characteristics of the performance portfolio. For inflation-linked liabilities, we find that the use of a minimum variance equity benchmark based on a double-sort procedure of stocks according to (high) dividend yield and (low) volatility would have generated, over the 1999–2012 period, an annualised excess return reaching 270 basis points for the same funding ratio volatility, as well as a lower funding ratio drawdown, compared to what is observed with the standard cap-weighted S&P 500 index as a benchmark.

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

The second definition is based on factor exposure matching. Since perfect cash-flow replication is typically difficult to achieve in practice, investors who need to hedge liabilities instead may aim at reducing exposures of their assets with those of their liabilities. The objective pursued in this case is to utilise the factor risk against vari-
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New Developments in Retirement Investing

Mass Customisation versus Mass Production in Retirement Investment Management: Addressing a "Tough Engineering Problem"

Funding Ratio Flaws

Facts about Factors

Hacking Reverse Mortgages

Ask a consultant? The role of investment consultants in pension fund governance

On the Asset Allocation of a Default Pension Fund

For more information, please contact Maud Gauchon on +33 493 187 887 or by e-mail at maud.gauchon@edhec-risk.com
1. Base case results on liability-friendly portfolios

<table>
<thead>
<tr>
<th>Panel A: Liability-friendliness indicators</th>
<th>No selection (CW)</th>
<th>No selection (EW)</th>
<th>High dividend yield</th>
<th>High correlation</th>
<th>Low volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tracking error (%)</td>
<td>18.8</td>
<td>19.9</td>
<td>17.9</td>
<td>17.4</td>
<td>14.6</td>
</tr>
<tr>
<td>Volatility (%)</td>
<td>17.3</td>
<td>17.3</td>
<td>16.2</td>
<td>16.2</td>
<td>13.0</td>
</tr>
<tr>
<td>Correlation (%)</td>
<td>1.46</td>
<td>-0.80</td>
<td>1.88</td>
<td>7.58</td>
<td>7.23</td>
</tr>
<tr>
<td>Average yearly dividend yield</td>
<td>3.58</td>
<td>2.94</td>
<td>5.85</td>
<td>3.70</td>
<td>4.59</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Performance indicators</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Annualised return (%)</td>
<td>10.9</td>
<td>13.3</td>
<td>13.8</td>
<td>14.6</td>
<td>13.2</td>
</tr>
<tr>
<td>Sharpe ratio</td>
<td>0.42</td>
<td>0.55</td>
<td>0.62</td>
<td>0.681</td>
<td>0.731</td>
</tr>
<tr>
<td>Turnover (%)</td>
<td>4.4</td>
<td>12.2</td>
<td>23.3</td>
<td>8.9</td>
<td>27.5</td>
</tr>
<tr>
<td>Conditional annualised return (%)</td>
<td>5.5</td>
<td>6.4</td>
<td>8.8</td>
<td>9.6</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel C: Liability-friendliness indicators of opposite selections</th>
<th>No selection (CW)</th>
<th>No selection (EW)</th>
<th>High dividend yield</th>
<th>High correlation</th>
<th>Low volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tracking error (%)</td>
<td>22.6</td>
<td>22.1</td>
<td>27.8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Volatility (%)</td>
<td>21.0†</td>
<td>20.1†</td>
<td>26.1†</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Correlation (%)</td>
<td>-1.1</td>
<td>-7.5†</td>
<td>-6.7†</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average yearly dividend yield</td>
<td>0.51</td>
<td>2.50</td>
<td>1.38</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel D: Performance indicators of opposite selections</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Annualised return (%)</td>
<td>11.3</td>
<td>12.4</td>
<td>10.7</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sharpe ratio</td>
<td>0.36†</td>
<td>0.43†</td>
<td>0.27†</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Turnover (%)</td>
<td>2.75</td>
<td>5.51</td>
<td>3.42</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Conditional annualised return (%)</td>
<td>3.3</td>
<td>5.1</td>
<td>1.8</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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

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

2. Base case results on liability-friendly portfolios

<table>
<thead>
<tr>
<th>Equity exposure</th>
<th>Volatility funding ratio for 40% equity allocation</th>
<th>Correlation with liabilities</th>
<th>Iso funding ratio equity allocation</th>
</tr>
</thead>
<tbody>
<tr>
<td>S&amp;P 500</td>
<td>40.0%</td>
<td>70.0%</td>
<td>38.1%</td>
</tr>
<tr>
<td>Minimum variance liability-friendly portfolio</td>
<td>40.0%</td>
<td>5.2%</td>
<td>491.9%</td>
</tr>
<tr>
<td>40.0%</td>
<td>5.2%</td>
<td>491.9%</td>
<td>54.0%</td>
</tr>
</tbody>
</table>

stocks, selecting the 100 lowest-volatility stocks among them, and subsequently performing a minimum-variance optimisation. Overall, we find that double sorts starting with DY and then low volatility generate comparable levels of factor-matching liability-friendliness (tracking error at 14.13) with improved cash-flow-matching properties (average DY at 5.40 compared to selection purely based on volatility).

Due to the resulting improvement in liability-hedging benefits, liability-driven investors can allocate a higher fraction of their portfolios to equities without a corresponding increase in funding ratio volatility (see figure 2). For example, we find that a pension fund allocating 40% to equities on the basis of a cap-weighted equity benchmark can allocate as much as 54% to a minimum-variance portfolio of selected stocks from the aforementioned double-sort procedure for the same volatility of the funding ratio (an increased allocation which we refer to as “iso funding ratio volatility equity allocation”). This substantial increase in equity allocation without a corresponding increase in ALM risk budgets confirms that the aforementioned improvements obtained in terms of improved liability-friendliness are economically significant.

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

The resulting increase in equity allocation for the same ALM risk budget, combined with an improved risk-adjusted performance of the
Alternative risk premia harvesting: From hedge fund replication to hedge fund substitution

Lionel Martellini, Professor of Finance, EDHEC Business School, Director, EDHEC-Risk Institute, Senior Scientific Advisor, ERI Scientific Beta; Jean-Michel Maeso, Quantitative Research Engineer, EDHEC-Risk Institute

There is a growing interest among sophisticated asset managers and asset owners in factor investing, a disciplined approach to portfolio management that is broadly meant to allow investors to harvest risk premia across and within asset classes through liquid and cost-efficient systematic strategies, without having to invest with active managers (see Ang [2014] for a comprehensive overview). While it is now well accepted that the performance of active mutual fund managers can, to a large extent, be replicated through a static exposure to traditional factors (see in particular the Ang, Goetzmann and Schaefer [2009] analysis of the Newhouse [2006] data which found a high degree of persistence in many traditional factors), the implication of these findings is that traditional risk premia can be most efficiently harvested in a passive manner, an outstanding question remains with respect to what is the best possible approach for harvesting alternative risk premia such as the currency carry factor or the commodity momentum factor.

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

Hedge fund replication with traditional and alternative factors

Benchmarking hedge fund performance is particularly challenging because of the presence of numerous biases in hedge fund return databases, the most important of which are sample selection bias, survivorship bias and
2. In-sample adjusted R-squared for empirical data

<table>
<thead>
<tr>
<th>Case 1: 19 factors</th>
<th>CA</th>
<th>CTA</th>
<th>DS</th>
<th>EM</th>
<th>EMN</th>
<th>ED</th>
<th>FIA</th>
<th>GM</th>
<th>LSE</th>
<th>MA</th>
<th>RV</th>
<th>SS</th>
<th>FoF</th>
</tr>
</thead>
<tbody>
<tr>
<td>19 factors</td>
<td>56</td>
<td>31</td>
<td>71</td>
<td>85</td>
<td>32</td>
<td>77</td>
<td>50</td>
<td>58</td>
<td>81</td>
<td>39</td>
<td>70</td>
<td>77</td>
<td></td>
</tr>
<tr>
<td>Traditional factors</td>
<td>49</td>
<td>12</td>
<td>42</td>
<td>52</td>
<td>-2</td>
<td>55</td>
<td>35</td>
<td>25</td>
<td>64</td>
<td>22</td>
<td>55</td>
<td>60</td>
<td>46</td>
</tr>
<tr>
<td>Economic factors</td>
<td>54</td>
<td>28</td>
<td>52</td>
<td>80</td>
<td>16</td>
<td>63</td>
<td>28</td>
<td>50</td>
<td>71</td>
<td>31</td>
<td>56</td>
<td>73</td>
<td>68</td>
</tr>
</tbody>
</table>

This table reports, for each hedge fund strategy, the linear regression adjusted R-squared of its monthly returns against different sets of factors (three cases) over the whole sample period ranging from January 1997 to October 2015.
the monthly excess return of hedge fund i at date t.
The hedge fund clone monthly return for strategy i is:
\[ \mu_{i,t}^{\text{clone}} = \sum_{k=1}^{K} \beta_{i,k} f_{k,t} + (1 - \sum_{k=1}^{K} \beta_{i,k}) r_{f,t} \]

Since our focus is on hedge fund replication, we take into account the possible leverage of the strategy by adding a cash component proxied by the US three-month Treasury bill index returns. A more sophisticated approach consists in explicitly modelling dynamic risk factor exposures through state-space variables via the Kalman filter. Broadly speaking, a state-space model is defined by a transition equation and a measurement equation as follows:

\[ \begin{align*}
\beta_t &= \beta_{t-1} + \eta_t \\
\epsilon_t &= \beta_t F_t + \epsilon_t
\end{align*} \]

(Transition equation)

(Measurement equation)

where \( \beta_t \) is the vector of (unobservable) factor exposures at time t to the risk factors, \( F_t \) the vector of factor monthly returns at time t, \( \epsilon_t \) and \( \eta_t \) are assumed to be normally distributed with a variance assumed to be constant over time. The hedge fund clone monthly return for strategy i is:

\[ \mu_{i,t}^{\text{clone}} = \sum_{k=1}^{K} \beta_{i,k} f_{k,t} + (1 - \sum_{k=1}^{K} \beta_{i,k}) r_{f,t} \]

The substantial decrease between in-sample (see figure 2) and out-of-sample (see figure 3) adjusted R-squared for all strategies suggests that the actual replication power of the clones falls sharply when taken out of the calibration sample. For example, the distressed securities, event driven and relative value clones have out-of-sample adjusted R-squared below 50% whereas their in-sample adjusted R-squared is above 70%.

To get a better sense of what the out-of-sample replication quality actually is, we compute the annualised root mean squared error (RMSE, see figure 3) which can be interpreted as the out-of-sample tracking error of the clone with respect to the corresponding hedge fund strategy. Our results suggest that the use of Kalman filter techniques does not systematically improve the quality of replication with respect to a simple rolling-window approach: the Kalman filter clones of the distressed securities, emerging markets, event driven, global macro, short selling and fund of funds strategies have root mean squared errors above their rolling-window clones. Overall, strategies like CTA global or short selling have clones with the poorest replication quality, with root mean squared errors superior to 7.5%. Overall, these results do not support the belief that hedge fund returns can be satisfactorily replicated.

From hedge fund replication to hedge fund substitution

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

We apply two popular robust heuristic portfolio construction methodologies, namely equal weight and equal risk contribution, using a 24-month rolling window for each hedge fund strategy relative to its bespoke subset of economically-identified risk factors in figure 1. The period considered is the out-of-sample period ranging from January 1999 to October 2015.

3. Out-of-sample adjusted R-squared and annualised root mean squared error (RMSE) for empirical data

<table>
<thead>
<tr>
<th></th>
<th>HF clone rolling-window adjusted R-squared (%)</th>
<th>HF clone Kalman filter adjusted R-squared (%)</th>
<th>HF clone rolling-window RMSE (%)</th>
<th>HF clone Kalman filter RMSE (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CA</td>
<td>38</td>
<td>47</td>
<td>4.8</td>
<td>4.4</td>
</tr>
<tr>
<td>CTA</td>
<td>81</td>
<td>77</td>
<td>4.9</td>
<td>5.8</td>
</tr>
<tr>
<td>DS</td>
<td>-4</td>
<td>20</td>
<td>4.0</td>
<td>5.0</td>
</tr>
<tr>
<td>EM</td>
<td>48</td>
<td>31</td>
<td>4.0</td>
<td>5.2</td>
</tr>
<tr>
<td>EMN</td>
<td>57</td>
<td>58</td>
<td>4.6</td>
<td>4.5</td>
</tr>
<tr>
<td>ED</td>
<td>-4</td>
<td>20</td>
<td>3.2</td>
<td>2.8</td>
</tr>
<tr>
<td>EVA</td>
<td>26</td>
<td>23</td>
<td>3.4</td>
<td>4.7</td>
</tr>
<tr>
<td>GM</td>
<td>-4</td>
<td>49</td>
<td>3.0</td>
<td>2.9</td>
</tr>
<tr>
<td>LSE</td>
<td>71</td>
<td>71</td>
<td>3.4</td>
<td>4.7</td>
</tr>
<tr>
<td>MA</td>
<td>-4</td>
<td>20</td>
<td>3.2</td>
<td>2.8</td>
</tr>
<tr>
<td>RV</td>
<td>46</td>
<td>49</td>
<td>3.0</td>
<td>2.9</td>
</tr>
<tr>
<td>SS</td>
<td>71</td>
<td>71</td>
<td>3.4</td>
<td>4.7</td>
</tr>
</tbody>
</table>

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

5. Sharpe ratios for empirical data

<table>
<thead>
<tr>
<th></th>
<th>HF clone rolling windows</th>
<th>HF clone Kalman filter</th>
<th>Equal risk contribution portfolio</th>
<th>Equal weight portfolio</th>
</tr>
</thead>
<tbody>
<tr>
<td>CA</td>
<td>0.36</td>
<td>0.31</td>
<td>1.21</td>
<td>1.13</td>
</tr>
<tr>
<td>CTA</td>
<td>0.42</td>
<td>0.37</td>
<td>0.55</td>
<td>0.37</td>
</tr>
<tr>
<td>DS</td>
<td>0.16</td>
<td>0.17</td>
<td>0.74</td>
<td>0.63</td>
</tr>
<tr>
<td>EM</td>
<td>0.39</td>
<td>0.30</td>
<td>0.25</td>
<td>0.40</td>
</tr>
<tr>
<td>EMN</td>
<td>0.47</td>
<td>0.74</td>
<td>1.02</td>
<td>0.96</td>
</tr>
<tr>
<td>ED</td>
<td>0.27</td>
<td>0.18</td>
<td>0.74</td>
<td>0.63</td>
</tr>
<tr>
<td>EVA</td>
<td>0.05</td>
<td>0.22</td>
<td>-0.25</td>
<td>0.37</td>
</tr>
<tr>
<td>GM</td>
<td>0.32</td>
<td>0.53</td>
<td>0.74</td>
<td>0.67</td>
</tr>
<tr>
<td>LSE</td>
<td>0.09</td>
<td>0.26</td>
<td>1.02</td>
<td>0.96</td>
</tr>
<tr>
<td>MA</td>
<td>0.32</td>
<td>0.39</td>
<td>1.02</td>
<td>0.96</td>
</tr>
<tr>
<td>RV</td>
<td>0.38</td>
<td>0.35</td>
<td>0.74</td>
<td>0.63</td>
</tr>
<tr>
<td>SS</td>
<td>-0.01</td>
<td>0.03</td>
<td>1.02</td>
<td>0.96</td>
</tr>
<tr>
<td>FOF</td>
<td>0.60</td>
<td>0.37</td>
<td>3.4</td>
<td>4.7</td>
</tr>
</tbody>
</table>

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

“Risk parity strategies applied to alternative risk factors could be a better alternative than hedge fund replication for harvesting alternative risk premia in an efficient way”

portfolio construction methodologies, namely equal weight and equal risk contribution, using a 24-month rolling window for each hedge fund strategy relative to its bespoke subset of economically-identified risk factors for the period January 1999–October 2015. We then compare the risk-adjusted performance of rolling-window and Kalman filter clones and the corresponding optimised portfolio of the same selected factors by calculating the out-of-sample Sharpe ratios for each fund strategy. The first two rows of figure 4 give the Sharpe ratios of the rolling-window and Kalman filter clones and the last two rows show the Sharpe ratios of the corresponding equal risk contribution and equal weight optimised portfolios. The clones for distressed securities, event driven, global macro, relative value and fund of funds have been built with the same six risk factors: equity, bond, credit, emerging market, multi-class value and multi-class momentum. The corresponding equal risk contribution and equal weight-optimised portfolios have respective Sharpe ratios of 0.74 and 0.63, which is higher than all of the previous clones’ Sharpe ratios (see for example the global macro and distressed securities Kalman filter clones with respective Sharpe ratios of 0.53 and 0.17). Similarly, the equity market neutral, merger arbitrage, long/short equity and short selling clones have been built with the same six risk factors: equity, equity defensive, equity size, equity quality, equity value and equity momentum. All the clones’ Sharpe ratios are lower (see for example the equity market neutral Kalman filter clone with Sharpe ratio of 0.74) than those of the corresponding equal risk contribution and equal weight-optimised portfolios (respectively 1.02 and 0.96), and sometimes substantially lower (see for example the merger arbitrage and long/short equity Kalman filter clones with respective Sharpe ratios of 0.39 and 0.26).

While the replication of hedge fund factor exposures appears to be a very attractive concept from a conceptual standpoint, our analysis confirms the previously documented intrinsic difficulty in achieving satisfactory out-of-sample replication power, regardless of the
New frontiers in retirement solutions

Lionel Martellini, Professor of Finance, EDHEC Business School, Director, EDHEC-Risk Institute, Senior Scientific Advisor, ERI Scientific Beta

New challenges in retirement investing
Over the last 15 years or so, the pension fund industry has experienced a series of profound structural changes. The shift in most accounting standards towards the valuation of pension liabilities at market rates, instead of fixed discount rates, has resulted in increased volatility for pension liability portfolios (see Fabozzi et al [2014] for a discussion of pension liability discounting rules). This new constraint has been reinforced in parallel by stricter solvency requirements that followed the 2000–05 pension fund crisis, while ever stricter solvency requirements are also increasingly being imposed on insurance companies in the US, Europe and Asia. This evolution in accounting and prudential regulations has subsequently led a large number of corporations to close their defined benefit pension schemes so as to reduce the impact of pension liability risk on their balance sheet and income statement. Overall, a massive shift from defined benefit to defined contribution pension schemes is taking place across the world. Consequently, individuals are becoming increasingly responsible for making investment decisions related to their retirement financing needs, investment decisions that they are not equipped to deal with given the low levels of financial literacy within the general population and the reported inability of financial education to significantly improve upon the current situation.

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

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

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

Some dramatic changes with respect to existing investment practices are needed to facilitate the development of such meaningful retirement solutions. Just as in institutional money management, the need to design an asset allocation solution that is a function of the kinds of particular risks to which the investor is exposed, or needs to be exposed to meet liabilities or fulfil goals, as opposed to purely focusing on the risks impacting the market as a whole, makes standard approaches (which are based on balanced portfolios invested in a mixture of asset class portfolios actively and passively managed against market benchmarks) mostly inadequate.

This recognition is leading to a new investment paradigm, which has been labelled goal-based investing (GBI) in individual money management (see Chhaabra [2005]), where investors’ problems can be fully characterised in terms of their meaningful lifetime goals, just as liability-driven investing (LDI) has become the relevant paradigm in institutional money management, where investing is a financial engineering device for generating meaningful dynamic allocation to these dedicated hedging portfolios and a common performance-seeking portfolio. In this sense, the GBI approach is formulated through the fund separation theorems that serve as founding pillars for dynamic asset pricing theory, just as was the case for the LDI approach (see also Shefrin and Statman [2000] and Das, Markowitz, Shefrin and Statman [2010] for an analysis of the relationship between modern portfolio theory portfolio optimisation with mental accounts in a static setting).

The framework should not only be thought of as a financial engineering device for generating meaningful investment solutions with respect to investors’ needs. It should also, and perhaps even more importantly, encompass a process dedicated to facilitating a meaningful dialogue with the investor. In this context, the reporting dimension of the framework should focus on updated probabilities of achieving investors’ meaningful goals and associated expected shortfalls, as opposed to solely focusing on standard risk and return indicators, which are mostly irrelevant in this context.

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

Within modern portfolio theory, mass customisation is trivialised: if investors’ problems can be fully characterised by a simple...
Are infrastructure firms different from other firms? Evidence from 15 years of UK data

Frédéric Blanc-Brude, Director, EDHECinfra; Majid Hasan, Head of Asset Pricing Modelling, EDHECinfra; Timothy Whittaker, Head of Data Collection, EDHECinfra

In a new paper drawn from the work of the EDHECinfra/ Meridiam/Campbell Lutyens research team, we study the characteristics of privately-held infrastructure investments, we conduct the first large-scale empirical analysis of the characteristics of cash flows in private infrastructure firms from the perspective of equity owners.

The paper addresses two main questions: do infrastructure firms correspond to a different business model than the rest of the firms active in the economy? And do infrastructure firms exhibit different equity payout behaviour from other firms?

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

References

Yale SOM — EDHEC-Risk Institute Certificate in Risk and Investment Management

This ambitious high-level programme in risk and investment management consists of four seminars that are intended to reflect the major steps in a modern investment process.

**Harvesting Risk Premia in Equity and Bond Markets Seminar**
9-11 May 2016 (London); 18-20 May 2016 (New Haven); and Q2 2017

**Harvesting Risk Premia in Alternative Asset Classes and Investment Strategies Seminar**
27-29 June 2016 (London); 11-13 July 2016 (New Haven); and Q3 2017

**Multi-Asset Multi-Manager Products and Solutions Seminar**
5-6 December 2016 (New Haven); 12-13 December 2016 (London); and Q4 2017

**Asset Allocation and Investment Solutions Seminar**
Q1 2017

Participants can complete all four seminars over a 1 to 2-year period and receive the prestigious joint Yale School of Management — EDHEC-Risk Certificate in Risk and Investment Management, or attend a single session, which provides more focused study.

For further information and registration, please contact Caroline Prévost at: yale-som-eri@edhec-risk.com or on: +33 493 183 496
In this first article, we address the first dimension of this question with a study of the dynamics of cash flows to private equity holders in infrastructure investments.

A unique new database

We are interested in the volatility of revenues in infrastructure firms as well as their relative correlation with macro factors such as GDP growth, inflation or market factors. We are also interested in the equity payout behaviour of infrastructure firms, relative to the business cycle as well as to other private and public firms in the UK.

This study makes use of the EDHECinfra infrastructure database: a collection of infrastructure cash flows provided by infrastructure investors and creditors, as well as manually collected annual reports. To date, the database covers more than 500 individual sets of infrastructure assets over 10 different countries, making it the most comprehensive database of infrastructure cash flows currently available. For this study, we focus on firms situated solely in the UK.

Our infrastructure cash flow data correspond to a sample of UK firms identified as being either special purpose vehicles created in the context of the financing of a specific infrastructure project, or a firm conducting specific infrastructure-related activities (such as a port or an airport) or a regulated utility.

The detailed accounts for each firm were obtained from infrastructure investors, lenders and companies. They were then analysed in order to classify each firm into one of three groups: contracted, merchant and regulated infrastructure (see Blanc-Brude [2013] for a detailed discussion of these different infrastructure business models).

Contracted infrastructure firms are not exposed to end-user demand. In the UK, the Private Finance Initiative (PFI) is the prime example of such projects. Under the PFI scheme, infrastructure investors have delivered a broad range of infrastructure, including schools, hospitals and prisons. Such projects generally spring from a long-term contract for the provision of an infrastructure asset or service between the public sector and private entity (the firm), by which the public sector commits to paying a regular income to the firm as long as the relevant infrastructure services are delivered according to a pre-agreed specification.

Merchant infrastructure firms in comparison are exposed to some degree of market risk. Such infrastructure projects can have long-term contracts supporting their revenue in the form of a power purchase agreement (PPA) or take-or-pay contract, but such contracts typically cover only part of the project’s capacity or lifespan. Other merchant infrastructure firms are fully exposed to end user demand and market prices; these include airports or toll roads.

Finally, regulated infrastructure firms are typically natural monopolies involved in the provision of essential services, such as sewage treatment, water distribution or power transmission. Such companies are regulated in the UK by independent agencies such as Ofwat or Ofgem.

The data span information from the early 1990s to 2015, as illustrated in figure 1.

We focus on UK data because they are

1. Number and time frame of reporting firms in the EDHECinfra database

Each line represents a time series of cash flow data

2. Estimates of the mean and variance parameters of the unit revenues and profits in calendar time for contracted infrastructure and matched control firms

1 See Blanc-Brude and Hasan (2015) for a theoretical approach to discount rate estimation in private infrastructure assets.

2 The UK company register.
To control for the effect of ownership structure and corporate governance on the behaviour of infrastructure firms, we build three control groups for each of our infrastructure firm types: private firms with concentrated ownership, private firms with dispersed ownership and public (listed) firms.

Each of these three control groups is ‘matched’ to the infrastructure firm of a given type using a ‘nearest neighbour’ methodology for total asset size, leverage and profitability and an exact match for “investment year” – i.e., the number of years since the creation of the firm. Hence, we test the difference in revenue and profit volatility as well as in payout ratio level and volatility of infrastructure investment using nine different tests: three types of infrastructure firms (contracted, merchant and utilities) against three types of corporate governance (private concentrated, private dispersed, public), while controlling for individual firm characteristics (size, leverage, profitability).

Such tests go a long way in addressing the matter of the ‘uniqueness’ of infrastructure investments. Indeed, if firm characteristics and corporate governance can be expected to explain in large part the business model and dividend payout behaviour of the firm, then for infrastructure to be unique and not easily replicable by combining other types of investments, it must correspond to a unique combination of firm characteristics and corporate governance. Likewise, the revenues of infrastructure firms can only create a unique form of exposure to economic factors if their business model is not an easily replicable combination of the business models of other firms.

Infrastructure is unique

We find that, as far as UK data show over the past 15 years, infrastructure firms are indeed truly unique: that is, after controlling for size, leverage and profitability, as well as the impact of the investment ‘lifecycle’, infrastructure firms exhibit lower revenue volatility and higher payout ratios (dividends to revenue) than any other group of private or public firms:

- Compared to their control groups, infrastructure firms have lower revenues and profits per dollar invested, highlighting the capital-intensive and long-term nature of their business.
- They are also characterised by significantly lower volatility of revenues and profits compared to their matched control groups, both at the aggregate level (all periods) and at each point in investment and calendar time.
- Infrastructure firms exhibit a very dynamic lifecycle compared to control groups, with unit revenues and profits evolving by an order of magnitude over the investment cycle.
- Regression analysis shows that infrastructure firms in general tend to be less sensitive to changes in revenues, profits, leverage or size:
  - More profitable firms tend to have higher revenues but this effect tends to be much smaller for infrastructure firms;
  - Firms with higher revenues tend to have higher profits; this effect tends to be much smaller than for control groups for contracted and merchant infrastructure firms, but it is much larger than for control groups in the case of regulated infrastructure firms;
  - Firms with higher leverage tend to have relatively lower revenues, but again this effect impacts infrastructure firms less and is not statistically significant for merchant infrastructure; such firms also tend to have relatively lower profits, but this effect is smaller for contracted infrastructure firms. However, the same effect is greater in private firms than in the control groups and it is not significant in regulated utilities.
  - Larger firms tend to have lower revenues, but only in the case of infrastructure private firms with concentrated ownership, and the effect is much larger for non-infrastructure firms. Larger firms, including infrastructure firms, also tend to have higher profits, but the effect is again much more muted than for control groups and it is not significant for merchant infrastructure.

“Infrastructure firms are indeed truly unique: that is, after controlling for size, leverage and profitability, as well as the impact of the investment ‘lifecycle’, infrastructure firms exhibit lower revenue volatility and higher payout ratios (dividends to revenue) than any other group of private or public firms.”

4. Estimates of the mean and variance parameters of the unit revenues and profits in calendar time for regulated infrastructure and matched control firms

Regression analyses also show that different proxies of the ‘business cycle’ have a strong statistical effect on profits and revenues in non-infrastructure firms, but that this effect is absent in the different infrastructure firm test groups – i.e., infrastructure firm revenues and profits are not correlated with the business cycle. Instead, the effect of the investment lifecycle is what explains the change in unit revenues and profits of infrastructure firms.

The probability of positive equity payouts in infrastructure firms is significantly higher than in any of the control groups, reaching as high as 80% after investment year 10 in contracted infrastructure and the 60–70% range in merchant and regulated infrastructure. Control groups never reach a (conditional) probability of payout higher than 40%.

Equity payout ratios in infrastructure firms are considerably higher than in control groups, reaching expected values of more than 10% of revenues when matched controls never pay out more than 5% of revenues.

Thus, as illustrated in figures 2 to 4, we find that infrastructure firms exhibit a truly unique business model compared to a large control group of public and private firms. We also report that the ‘contracted’ type of infrastructure investments is so unique that it cannot
The cash flow dynamics of private infrastructure project debt: New results using a new infrastructure cash flow database

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In a new paper drawn from the EDHECinfra/NATIXIS research chair on infrastructure private debt, we document the statistical characteristics of debt service cover ratios (DSCRs), which measure the amount of cash available to make the current period’s debt service in private infrastructure debt payments.

Indeed, robust and well-calibrated models of DSCR dynamics are an important part of the objective to create investment benchmarks of private infrastructure debt, as described in the EDHECinfra roadmap (Blanc-Brude [2014]).

In a previous paper (Blanc-Brude, Hasan and Ismail [2014]), we showed that debt service cover ratios can play a pivotal role in the modelling of credit risk in fixed income infrastructure investments because DSCRs provide us with:

- An unambiguous definition of the point of hard default (default of payment) – ie, DSCR = 1, and
- An equally unambiguous definition of key technical default covenants – ie, DSCR = 1 – x – while both types of default events create significant embedded options for creditors following a credit event.

Moreover, knowledge of DSCR dynamics is sufficient to estimate the firm’s distance to default (DD), which is the workhorse of the so-called Merton or structural credit risk model. DSCR dynamics can also be combined with future debt service to compute the expected value and volatility of the firm’s future cash flow, which is instrumental in measuring enterprise value in the case of infrastructure projects, since they derive their value almost entirely from future operating cash flows.

For this purpose, we collect a large sample of realised DSCR observations across a range of infrastructure projects spanning more than 15 years, representing the largest such sample available for research to date, and conduct a series of statistical tests and analyses to establish the most adequate approach to modelling and predicting future DSCR levels and volatility.

Using these results, we build a model of the conditional probability distribution of DSCRs at each point in the life of infrastructure projects.

A combination of empirical analysis and statistical modelling is necessary. DSCRs in infrastructure project finance are mostly undocumented both in industry and academic empirical literature. While DSCR information is routinely collected by the creditors of infrastructure projects, this type of data is typically confidential and not available in large datasets.

From such data paucity, especially in time series, it follows that empirical observations alone are not sufficient to document the expected behaviour of infrastructure project cash flows over their entire investment life, and a combination of ex ante modelling and empirical observations is necessary.

Finally, private infrastructure investment tends to be characterised by very large individual investments, almost necessarily leading to poorly diversified portfolios. This suggests that assuming the mean-reversion of investors’ infrastructure debt portfolios may not be realistic and that idiosyncratic risk should be taken into account.

In particular, individual infrastructure investments can exhibit significant ‘path dependency’ and investors cannot necessarily take for granted the notion that they are exposed to the ‘median infrastructure project’.

For both sets of reasons (data limitations and the importance of firm-specific risk), an adequate model of the DSCR should be able to capture conditional dynamics and explicitly integrate the different credit ‘states’ that an infrastructure project might go through.

This can help both to learn from the data as and when it becomes available, and to take into account the path-dependency of each instrument when estimating future cash flows, instead of assuming a reversion to the population mean.

Current academic and industry literature is static in nature and relies on ‘reduced form’ credit models, which are likely to be biased given the nature of empirical data available and, in the current state of empirical knowledge, can only address a limited number of dimensions of private infrastructure debt investment: the historical frequency of default events, and to some extent, average recovery rates.

For these reasons, in our research we endeavour to better document the dynamics of DSCRs in infrastructure project finance and build a model of DSCR dynamics using Bayesian...
inference to describe credit state transitions and to estimate the mean and variance of the DSCR in each state and at each point in an instrument’s life. This allows better prediction of defaults, conditional on the actual trajectory of individual investments or groups of projects. The ability to predict cash flows and their volatility is then instrumental in the implementation of the private infrastructure debt valuation model defined in Blanc-Brude, Hasan and Ismail (2014).

### Dividing infrastructure investments into groups defined by their ‘breathing rate’

In Blanc-Brude, Hasan and Ismail (2014), we described two generic and intuitive types of infrastructure project companies and called them ‘contracted’ and ‘merchant’.

- **Contracted projects** are those receiving contracted income.
- **Merchant projects** (those receiving market/spot income) are exposed to market-related uncertainties (e.g., in the case of merchant infrastructure).

The two groups correspond to two distinctive DSCR processes, with statistically different mean and variance parameters and following different project time dynamics. We also find, as intuition predicts, that contracted infrastructure projects are more resilient to default, and those exposed to merchant or commercial projects (those receiving contracted income) are much less affected by macro-variables or the business cycle than merchant projects.

We confirm our hypothesis that the DSCR profile of an infrastructure project is strongly related to the riskiness of its business model and that DSCR data for more than 200 projects in Europe and the US covering our two broad categories of projects is available for research to date.

#### Our dataset of realised DSCRs is built using data available for research to date

Our initial analysis of the data reveals that the DSCR profiles of individual projects are highly non-linear, auto-regressive and heteroskedastic (variance is not constant).

Hence, a more advanced model that can capture these dynamics is needed.

### Tracking the ‘coordinates’ of the DSCR distribution in the mean-variance state-space

If the DSCR, is serially correlated and can change profile during the investment lifecycle of infrastructure projects, the ex post trajectory of individual projects could in principle correspond to any combination of high/low expected value (DSCRs) and high/low volatility (−DSCR). The DSCR of populations of projects would equally reflect the weighted trajectory of their constituents in a DSCR, mean/variance ‘plane’.

Numerous models exist that aim to determine the position of a dynamic system and, based on the latest round of observations, to predict where it will be positioned in future periods. Such systems are frequently used in robotics, aero-spatial and chemistry applications. In our context, one such approach is to estimate the position of a given infrastructure project in a mean/variability DSCR plane at a given point in time, and to predict its position, its DSCR mean and variance ‘coordinates’ so to speak, in future periods.

In the descriptive part of our analysis of the data, we show that realised DSCRs can be fitted to a lognormal process up to their 90th and 85th quantiles for contracted and merchant projects, respectively, at each point in their lifecycle, which allows us to develop an easily tractable model of parameter inference.

Hence, we propose a two-step modelling strategy combining a three-state model corresponding to the different phases of a project’s life and the otherwise lognormal dynamics of the DSCR, with a filtering model to infer the values of the lognormal process parameters (its ‘coordinates’) in the state in which the DSCR is indeed lognormal.

### Three-state transition probabilities

The DSCR process is assumed to occur in any one of three states at time t: a risky state (R) if the DSCR is below a threshold corresponding to DSCR = 1 in which the DSCR process stops until it emerges from default; and a safe state (S), corresponding to DSCR being above the ‘good-lognormal-fit’ quantile, in which case, as long as the DSCR stays in that state, the project debt is considered risk-free.

Hence, once a project’s DSCR breaches the hard default threshold represented by DSCR = 1, it enters the default state, which it may or may not leave after a number of periods. In this state, creditors can either default or engage in negotiations with the project sponsors in order to restructure the firm and its debt, or indeed take over the firm and seek another sponsor (see Blanc-Brude, Hasan and Ismail 2013).

Hence, the firm may transit out of the default state into the risky state with some probability (say, 𝜋₁), or out of the default state into the safe state (S) with some probability (say, 𝜋₂).

In this state, the DSCR process effectively stops (in most cases short at no debt service), hence estimating its mean and variance is irrelevant since the project is already in default.

In the safe state, on the contrary, the realised DSCR is so high that no matter how volatile the process might be to the upside, the perspective, the probability of default is not significantly different from zero. The debt is (conditionally) risk-free. As before, in expectation at time t, an infrastructure project may transit in and out of the default state with each point in the future, with some probability (say, 𝜋₃).

In this state, estimating the parameters of the DSCR distribution, in particular estimating its variance, is also irrelevant.

Finally, in between the default and safe states, a project’s DSCR may take values between 1 and some higher threshold DSCR = 𝜃. From this state, it may either stay in the risky state or transit out of it into the state of default ‘D’ or the safe state ‘S’, both described above.

In this state, we know from our empirical results that if the upper threshold is set at the 85th/90th quantile, the data follows a lognormal process, the parameters of which (position and scale) have to be estimated.

Formally, this set-up amounts to relatively simple probability models of compound distributions, which can be set in terms of a series of binomial draws and calibrated using Bayesian inference given some prior knowledge (eg, we know from credit rating studies that projects tend to stay in the default state and counting the number of projects crossing the different state thresholds, conditional on which state they are in at the previous period.

The combination of the conditional probabilities (in each case, being in the same state at time t) is then combined into the probability of being in any given state at time t.

For contracted projects the probability of being in the risky state is much higher compared to the probability of being in the default state – ie, contracted projects are more likely to stay in the ‘normal’ risky state.

For merchant projects, the probability of being in the risky state is lower, while the probabilities of being in the default and safe states are higher compared to the corresponding probabilities for contracted projects. Thus, merchant projects are found to have more diverse DSCR trajectories in state space, and each state is less persistent (stable).

This result confirms that path dependency can be an important dimension of infrastructure investment insofar as assets are more or less heterogeneous and it can be difficult to fully diversify very large and bulky assets. For instance, our results suggest that contracted infrastructure is more homogenous than...
merchant projects, which are more likely to follow paths that diverge strongly from the mean of the population.

**Group and individual DSCR trajectories**

To determine the value of the lognormal process parameters in the ‘risky’ state discussed above, we propose to use a straightforward implementation of so-called particle filtering models to infer the parameter values of the DSCR’s lognormal process in the risky state – i.e., the state in which documenting and tracking the volatility of the DSCR really matters, because it is a direct measure of credit risk.

Filtering models are a form of signal processing and aim to arrive at some best estimate of the value of a system, given some limited and possibly noisy measurements of that system’s behaviour. Given our modelling objectives to accommodate small samples, and to avoid assuming static values for the distribution parameters, we must be able to revise any existing parameter estimates once new data becomes available. This process is best estimated iteratively using Bayesian inference techniques described in detail in our paper.

We show that such a framework allows the dynamics of DSCR to be derived in well defined groups of projects as well as individual projects, including tracking the individual DSCR ‘path’ followed by investments that do not necessarily correspond to the median infrastructure project.

The estimated dynamics of the DSCR process in contracted and merchant projects is shown in figure 1, which describes the change in density of the DSCR process in investment time, and figure 2, which describes the trajectory of the DSCR state in the mean/standard deviation plane.

From such results, certain credit risk conclusions are immediately available, such as the expected default frequency for hard defaults, but also any level of technical default (DSCR = 1.x) as shown in figure 3.

These results allow us to characterise the behaviour of groups of infrastructure projects which exhibit reasonably homogeneous dynamics; however, we know that highly idiosyncratic trajectories and path dependency should be a point of interest in a context where diversification is difficult to achieve in full.

Hence, we also show that the ability to infer both the expected value and the volatility of the DSCR process allows us to take a much more informed view on the credit risk of projects that substantially deviate from their base case.

For instance, consider an infrastructure project that follows an oft-observed trajectory: while it remains in the risky state throughout its life, it starts off with a relatively high DSCR, implying a merchant-type structure with relatively high DSCR volatility, but later on undergoes a large downward shift in its realised DSCR level – e.g., as the result of a negative demand shock, while its DSCR realised volatility from that point onwards also decreases markedly.

A concrete case of such a trajectory could be a toll road experiencing significant loss of traffic after an economic recession, but for which the residual ‘baseload’ traffic is much less volatile than before the shock, and still sufficiently high to keep the DSCR out of the default state.

Such a project would not be adequately captured by the mean DSCR process of its original family, even though this was the best available starting point to anticipate its behaviour at $t_c$.

In this illustration, we know the ‘true’ underlying DSCR process that is otherwise unobservable, and how it is impacted by the negative demand shock. The point of the example is to
show that as we observe realised information for individual investments, our estimates of the true process can quickly converge to the true value and then track it as it evolves during the life of the investment.

Figure 4 shows the filtered DSCR mean and standard deviation along with the realised DSCR values and the true standard deviation of the project. As soon as the DSCR diverges from its original trajectory the model takes this new information into account, and if the divergence persists, future estimates of the expected value of DSCR, are updated accordingly. Likewise, initial estimates of the volatility of DSCR, on the right panel of figure 4 are corrected as information about the lower realised volatility becomes integrated into each posterior value.

In our example, the ability to revise the DSCR dynamics of individual projects directly leads to the revision of their risk metrics, of the probabilities of dividend lockup, soft default, and hard default, respectively, and suggests that the negative jump in the DSCR, combined with lower realised volatility of DSCR, has no noticeable effect on the project’s probability of hard default, a negligible impact on probability of soft default, but a noticeable impact on the probability of a dividend lockup.

Towards large samples of DSCR data

Our research shows that a powerful statistical model of credit ratio dynamics can be developed, which can provide important insights for the valuation of private credit instruments in infrastructure project finance.

It also militates for standardising the data collection and computation of items such as the debt service cover ratio in infrastructure project finance, and for pooling this information in central repositories where it can be used to create the investment metrics that investors need (and regulators require) to be able to invest in large, illiquid assets such as private infrastructure project debt.

Such analyses will be further developed as new data is collected and standardised to improve our ability to track the DSCR path of individual and groups of infrastructure projects, and increase the number of control variables and the robustness of parameter estimates.

EDHEC is committed to the continued development of this research agenda, both in terms of data collection and technological development. 

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References

Hedge funds: From leading edge to bleeding edge, and back

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Hedge funds are booming. With $2.9tn of assets under management and close to 9,000 managers, what used to be an old cottage industry run by talented investors has gradually morphed into an asset management industry run by businessmen. Today, some of the largest asset managers continuously expand their offerings and launch new hedge funds and new strategies on a regular basis. Smaller and mid-size managers who are starved of assets try to grow so fast that they can finance more investors with their core offerings. All face additional regulations, demands for greater transparency, pressure on fees, squeezes on operating margins and, more importantly, difficult market conditions and increased competition. Despite this, investors in search of returns that are uncorrelated to traditional equity and bond markets still plough more money into the hedge fund industry. Are they right? Or will they likely be disappointed?

More beta...

If we go back to their roots, hedge funds were supposed to hedge market risk. At least, this is what Alfred Winslow Jones used to pitch to his investors in 1949, as his investment approach combined long and short positions to create a market-hedged portfolio. Unfortunately, Jones’s successors have been far less disciplined. As illustrated in figure 1, at the industry level (as measured by the HFRI Fund Weighted index), the S&P 500 used to explain 0.2% of returns in 1993. This number gradually increased to 25.7% in 2000, 50.9% in 2010, and peaked at 58.8% in 2015. Stated differently, the majority of hedge fund returns in aggregate is now explained by equity markets.

Of course, one could argue that hedging has been costly, particularly during the recent bull markets, so hedge funds were right to reduce their hedges and become more directional on equities. As an investor, our answer will be simple: if there is a structural long equity beta in a hedge fund, then it should be disclosed and...
...and less alpha
Historically, hedge funds were supposed to generate some alpha. Here again, while Alfred Winslow Jones has delivered, his successors seem to have forgotten this fundamental goal. While the monthly after-fee average alpha generated by hedge funds was around 1.25% in the early 1990s, this number has fallen dramatically over the years and is today barely positive – see figure 2. A similar declining trend can be observed for funds of hedge funds in aggregate.

Cynics will observe that the situation has recently improved, with a small recovery that has brought alphas out of negative territory. Dead-cat bounce or double-bottom base? Tough to say, but what is clear is that the current level of average alpha is far below the average level of fees charged by hedge funds.

Is an industry average relevant?
While these numbers are not really reassuring, investors need to understand that they represent the average of the aggregate hedge fund industry. Should one care – just maybe greedier.

hedge fund industry is hugely asymmetric. On one side, 58% of the managers only represent 0.11% of the total industry assets – they run a hedge fund which has less than $10m in assets, far too small to attract institutional clients or to develop an adequate infrastructure. These managers could disappear overnight and the market would not necessarily realise it. On the other side, 6.52% of the managers run multi-billion-dollar funds that represent in aggregate 82% of the total industry assets. This huge asymmetry makes the behaviours of the average hedge fund radically different from the behaviour of the average dollar managed.

Second, in our opinion, there is no reason to expect hedge funds to be attractive in aggregate. If a staggering 85% of active large-cap fund managers fail to beat their benchmarks year after year, why should things be different for hedge funds? Particularly when one remembers it is easier to create a hedge fund than a mutual fund, and that hedge fund returns have in addition to support a 2% management fee and a 20% performance fee? On average, asset managers are average, minus their fees. And hedge funds managers are no different – just maybe greedier.

It is therefore not surprising to read in the latest Eurekahedge report that just 58% of hedge fund managers turned a profit in 2015, the worst performance since 2011, with 15% of them posting losses of more than 8%.

Third, nobody really invests in an index of several thousand hedge funds. Using it as a benchmark to estimate the quality of the ‘asset class’ is therefore introducing a severe bias in the assessment.

When common sense helps
With equities entering a bear market and bonds approaching their collapse, we believe it is a good time for all investors to rethink their allocation to hedge funds. However, in order to obtain some alpha, a number of basic rules need to be remembered. Let us briefly discuss three of them.

Hedge funds are about finding talented managers, not about the industry or the strategy. An interesting illustration of this is given by our global macro allocation, which made money after fees every single year since our inception in 2002, while the HFRX Global Macro index has been positive in only one out of the past seven years. Needless to say, while we are negative on the global macro industry, we are positive on our global macro managers going forward. Another example is our equity long/short allocation, which only counts four managers but was positive in dollar terms in 2015, despite difficult market conditions.

Unusually careful through diversification destroys hedge fund alpha. This statement is not new; it was proven by Markowitz in the 1950s and it forms the basis of modern portfolio theory. The more managers one adds in a portfolio, the more likely the specific bets of these managers will cancel each other out, while fees will pile up. The worst happens when manager A shorts a stock and manager B buys the same stock, fees charged by hedge funds.

Performance fees are much needed to justify fees charged by hedge funds. Second, higher fees should generally come with higher volatility in order to produce higher gross returns, and ultimately, higher net returns. As a quick test, one can assume a long-term Sharpe ratio equal to one, and test what the required level of gross returns and volatility is in order to generate one’s target net return. If the result seems infeasible, just walk away. A number of hedge funds have unfortunately good Sharpe ratios, but very low volatility, high fees, and as a result, disappointed investors.

Some will say that all these rules are more common sense than financial theory. They are right. Common sense is usually a smart start to investing in hedge funds.

The views expressed in this article are those of the author exclusively.

Reference