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AsianInvestor

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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.

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Introduction

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

We compare different approaches to the design of factor indices in the equity space, notably concentrated indices and more diversified indices. Overall, it appears that concentrated factor tilts lead to implementation challenges that are not compensated by better risk-adjusted returns.

We then provide perspective on misconceptions about performance drivers by drawing on conceptual considerations and empirical evidence. The analysis shows that, more often than not, superficially convincing claims about smart beta performance drivers stand on shaky foundations.

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.

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. 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 beyond standard product-based market-centred approaches and to start providing both institutions and individuals with meaningful retirement investment solutions. There is currently a unique opportunity for the financial industry to add value for society as a whole.

Drawing on research from the Meridiam/Campbell-Lutyens research chair at EDHEC*infra*, we conduct the first large scale empirical analysis of the characteristics of cash flows in private infrastructure firms from the perspective of equity owners and find that infrastructure firms exhibit a truly unique business model compared to a large control group of public and private firms.

On the subject of the cash flow dynamics of private infrastructure project debt, as part of the Natixis research chair at EDHEC*infra*, we produce new results using a new infrastructure cash flow database. Our research shows that a powerful statistical model of credit ratio dynamics can provide important insights for the valuation of private credit instruments in infrastructure project finance.

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

Noël Amenc

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Concentrate or Diversify – What is the Best Way to Gain Factor Exposure?

By Noël Amenc, Professor of Finance, EDHEC-Risk Institute, CEO, ERI Scientific Beta; Frédéric Ducoulombier, Business Development Director, Asia-Pacific ex Japan, ERI Scientific Beta; Felix Goltz, Head of Applied Research, EDHEC-Risk Institute, Research Director, ERI Scientific Beta and Sivagaminathan Sivasubramanian, Quantitative Research Analyst, ERI Scientific Beta

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 efficiently diversify unrewarded risks due to excessive concentration in the largest-market-cap stocks. Several studies (see e.g. 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 backseat 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 exposures. Such capturing of risk premia associated with systematic factors is attractive for

investors who can accept the systematic risk exposure in return for commensurate compensation.

However, factor-tilted strategies, when they are very concentrated, may also take on other, non-rewarded, risks. Non-rewarded risks come in the form of idiosyncratic or firm-level risk, as well as potential risk for sector concentration. Financial theory does not provide any reason why such risk should be rewarded. Therefore, a sensible approach to factor investing should not only look 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

‘In recent years, the question of diversification has taken a backseat to the question of appropriate factor tilts, which has become the prime concern of smart beta providers.’

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 investing¹: “In the investor's list of common stocks there are bound to be some that prove disappointing... But the diversified list itself, based on the above principles of selection [...] should perform well enough across the years. At least, long experience tells us so.” Aiming at a highly-concentrated value portfolio would be completely inconsistent not only with financial theory, but also with the principles put forth by the early advocates of value investing.

When constructing portfolios which contain, for example, a large number of value stocks, cap-weighted portfolios of value stock selections may at first seem to be more neutral implementations than

equal-weighted portfolios. However, it is well known that cap-weighting has a tendency to lead to very high concentration given the heavy-tailed nature of the distribution of market cap across stocks in the same universe. It is well documented in the academic literature that simple cap-weighted value-tilted portfolios have not led to attractive performance. In fact, across different studies (see e.g. Fama and French (2012, 2015)), empirical results show that a value strategy needs to be well-diversified to deliver a significant premium. For example, the standard Fama and French value factor includes a broad selection of stocks, and uses a two-tiered weighting approach to obtain better diversification. In particular, the value factor is an equal-weighted combination of sub-portfolios for different market cap ranges, effectively overweighting smaller size stocks and increasing the effective number of stocks. The fact that the most widely-cited research documenting the relevance of the value factor does not use simple cap-weighted factors, but rather constructs more balanced portfolios, shows the lack of support for industry practices using simple cap-weighted factor 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 weighting schemes – cap weighting (CW) and equal weighting. 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.¹ To construct factor-tilted portfolios, the top

¹ As cited by Asness *et al.* (2015)

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 4 weeks; Low Volatility: standard deviation of weekly stock returns over the past 104 weeks; Low Investment: past 2-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. This is done because, by definition, they measure their degree of being large cap, high volatility and high investment stocks respectively and we are interested in the stocks with opposite characteristics.

Exhibit 1: Performance of Cap Weighted and Equal Weighted Factor Indices

The time period of analysis is 31-Dec-1974 to 31-Dec-2014 (40 years). All figures reported are average figures across six factors – size, momentum, low volatility, value, low investment, and high profitability. All factor-tilted portfolios are rebalanced annually on the 3rd Friday of June, except Momentum-tilted portfolios, which are rebalanced semi-annually. The analysis is done using weekly total returns (dividends reinvested) in USD. The portfolios are constructed using a US stock universe that contains the 500 largest stocks by total market cap. The market-cap-weighted index of these 500 stocks is the benchmark. The yield on secondary market US Treasury Bills (3M) is the risk-free rate. All risk and return statistics are annualised and the Sharpe ratio and information ratio are computed using annualised figures. Outperformance probability (3 years) is the probability of obtaining positive relative returns if one invests in the strategy for a period of 3 years at any point during the history of the strategy. It is computed using a rolling window of length 3 years and step size 1 week. Average relative returns in positive (negative) periods is the mean of only positive (negative) rolling 3-year annualised relative returns. Extreme relative returns in positive (negative) periods are the 95th (5th) percentile of only positive (negative) rolling 3-year annualised relative returns. Data sources: CRSP and WRDS.

		Broad	Top 50% Stocks Selected by Factor Score		Top 20% Stocks Selected by Factor Score	
		Cap Weighted	Cap Weighted	Equal Weighted	Cap Weighted	Equal Weighted
Ann. Returns		12.26%	13.87%	16.01%	14.99%	16.62%
Ann. Volatility		16.09%	16.04%	16.64%	17.12%	17.37%
Sharpe Ratio		0.44	0.55	0.66	0.58	0.67
Ann. Rel. Returns		-	1.61%	3.75%	2.73%	4.36%
Ann. Tracking Error		-	4.61%	5.74%	7.53%	7.79%
Information Ratio		-	0.33	0.66	0.36	0.56
Outperf. Probability (3Y)		-	68.12%	76.04%	70.06%	72.94%
Positive Periods	Avg. Rel. Ret.	-	3.22%	5.60%	5.33%	7.05%
	Extreme Rel. Ret.	-	7.96%	13.63%	12.47%	16.32%
Negative Periods	Avg. Rel. Ret.	-	-2.35%	-3.92%	-3.56%	-3.89%
	Extreme Rel. Ret.	-	-6.71%	-9.94%	-9.24%	-9.48%

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 factor-tilted portfolios are rebalanced annually on the third Friday of June except that of 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 CRSP and WRDS. The long/short factor returns used for regression are obtained from Kenneth French's data library.³

Performance comparison of concentrated and diversified factor-tilted portfolios

Diversification leads to superior performance

Exhibit 1 shows a detailed comparison between heavily-concentrated (CW) portfolios and diversified (EW) portfolios. In the long run, on average, across the six factor tilts, the risk-adjusted performance of the 50% CW portfolio is inferior to that of the 50% EW portfolio. The average Sharpe ratio goes up from 0.55 to 0.66 when moving from CW to EW portfolios. Also, in the case of this narrow stock selection, the improvement in Sharpe ratio from 0.58 to 0.67 is observed through the use of EW over CW portfolios. Similarly, the information ratio remains higher for EW factor-tilted portfolios.

Increasing factor concentration by selecting the top 20% stocks in terms of factor scores instead of the top 50% stocks does not have a meaningful impact on risk-adjusted returns. For a given weighting scheme, increasing concentration through more stringent stock selection (i.e. going from 50% to 20%) leaves the average Sharpe ratios and information ratios at relatively similar levels overall. Thus there is no added value, from a risk-adjusted performance perspective, in having factor-tilted portfolios that are more

concentrated. We feel that this result is extremely important given the tendency observed on the market to produce extremely concentrated factor indices or portfolios.

Concentration leads to higher idiosyncratic risk

Exhibit 2 shows the idiosyncratic risk measures of the various factor-tilted portfolios based on the standard Carhart four-factor model. The use of this model enables the rewards of the different factor exposures of a long-only index or portfolio, which are never pure, to be taken into account. Moreover, to assess the reduction in volatility, we constructed a factor benchmark that invests in a portfolio with the same Carhart betas as the factor-tilted test portfolio, using leverage to obtain the same level of return. It is evident that, irrespective of the weighting scheme chosen, the residual risk is larger in the case of narrow stock selection. The average standard deviation of regression residuals increases upon moving from the broad 50% to the narrow 20% stock selection; from 0.51% to 0.82% for CW, and 0.61% to 0.79% for EW. The

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

Exhibit 2: Diversification Effects in Cap-Weighted and Equal-Weighted Factor Indices

The time period of analysis is 31-Dec-1974 to 31-Dec-2014 (40 years). All figures reported are average figures across six factors – size, momentum, low volatility, value, low investment, and high profitability. All factor-tilted portfolios are rebalanced annually on the 3rd Friday of June except Momentum-tilted portfolios, which are rebalanced semi-annually. The analysis is done using weekly total returns (dividends reinvested) in USD. The portfolios are constructed using a US stock universe that contains the 500 largest stocks by total market cap. The market-cap-weighted index of these 500 stocks is the benchmark. The yield on secondary market US Treasury Bills (3M) is the risk-free rate. A Carhart 4-factor model is used for regression. The reported alpha is annualised. Change in Specific Volatility is the difference between the volatility of the leveraged factor benchmark and its respective portfolio. The market factor is the excess returns of the cap-weighted benchmark over the risk-free rate. The size, value, and momentum factors are obtained from Kenneth French's data library. Data sources: CRSP and WRDS.

	Top 50% Stocks Selected by Factor Score		Top 20% Stocks Selected by Factor Score	
	Cap Weighted	Equal Weighted	Cap Weighted	Equal Weighted
Residual Std. Deviation	0.51%	0.61%	0.82%	0.79%
Interquartile Range of Residual Returns	0.52%	0.62%	0.88%	0.89%
Ann. Alpha	0.68%	1.42%	1.12%	1.53%
Ann. Alpha / Residual Std. Dev.	1.24	2.34	1.30	1.92
Change in Specific Volatility	-1.25%	-2.16%	-1.49%	-1.86%

interquartile range of the residuals is also higher in the case of the narrow 20% stock-selection portfolios, which shows that the portfolio's idiosyncratic risk increases as the number of stocks falls.

Annualised alpha per unit of residual standard deviation, which is a measure of unexplained idiosyncratic risk-adjusted performance, increases on average from 1.24 in the case of 50% CW to 2.34 in the case of 50% EW factor-tilted portfolios. Similarly, the reduction in volatility with respect to their respective factor benchmarks is higher for EW factor-tilted portfolios than for CW factor-tilted portfolios.

These results confirm that, contrary to widespread opinion, well-diversified factor portfolios or indices outperform their highly 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. Exhibit 3 shows that switching from a 50% CW factor-tilted portfolio to EW

‘From a risk-adjusted performance perspective, there is no added value in having factor-tilted portfolios that are more concentrated.’

brings fewer implementation challenges than switching to a narrower 20% stock selection while remaining cap-weighted. On average, turnover does not show any considerable increase when moving from a 50% CW factor-tilted portfolio to a 50% EW factor-tilted portfolio. The average turnover of 50% CW factor-tilted portfolios is 29.25% while that of 50% EW portfolios is 32.58%. On the other hand, switching to 20% CW factor-tilted increases the average turnover by a high margin; from 29.25% to 48.15%.

This is an interesting finding because when applied to a full universe without a factor tilt, EW is known to increase turnover. In the case of factor-tilted

indices, the turnover is mainly generated by variations in stocks' characteristics and thus changes in which stocks are selected. Therefore, the weighting scheme does not contribute much additional turnover.

Due to their nature of strongly underweighting smaller stocks, cap-weighted portfolios exhibit low Days-to-Trade (DTT) numbers.⁴ DTT is an indicator of the time required to trade the least 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, Goltz and Gonzalez (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

⁴ Days to Trade or DTT of a stock is the number of days required to trade total stock position in the portfolio of \$1billion, assuming that 10% of 'Average Daily Traded Volume (ADTV)' can be traded every day. For each portfolio, the reported DTT value is the 95th percentile of DTT values across all 10 annual rebalancings in the period 31-Dec-2004 to 31-Dec-2014 and across all stocks.

Exhibit 3: Implementation of Cap-Weighted and Equal-Weighted Factor Indices

All figures reported are average figures across six factors – size, momentum, low volatility, value, low investment, and high profitability. All factor-tilted portfolios are rebalanced annually on the 3rd Friday of June except Momentum-tilted portfolios, which are rebalanced semi-annually. The analysis is done using weekly total returns (dividends reinvested) in USD. The portfolios are constructed using a US stock universe that contains the 500 largest stocks by total market cap. The market-cap-weighted index of these 500 stocks is the benchmark. The reported Turnover is Annual 1-Way Turnover and is averaged over 40 annual rebalancings in the period 31-Dec-1974 to 31-Dec-2014. Days to Trade or DTT of a stock is the number of days required to trade total stock position in the portfolio of \$1billion, assuming that 10% of 'Average Daily Traded Volume (ADTV)' can be traded every day. For each portfolio, the reported DTT value is the 95th percentile of DTT values across all 10 yearly rebalancings in the period 31-Dec-2004 to 31-Dec-2014 and across all stocks. Data sources: CRSP and WRDS.

	Broad	Top 50% Stocks Selected by Factor Score		Top 20% Stocks Selected by Factor Score	
	Cap Weighted	Cap Weighted	Equal Weighted	Cap Weighted	Equal Weighted
Ann. 1-Way Turnover	2.68%	29.25%	32.58%	48.15%	48.64%
Days-to-Trade	0.20	0.82	1.56	1.41	2.35

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 groups of stocks. Moreover, it is well known 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 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 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.

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The Performance Drivers of Smart Beta – Facts and Fiction

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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 and traditional passive management. 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)⁵ analyse ten 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*”⁶. 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, i.e. 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, they result from 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 true alpha in the sense of added value of active management.

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)⁷ 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

⁵ Amenc, N., F. Goltz and J. Ulahel, 2016, Ten Misconceptions about Smart Beta, ERI Scientific Beta working paper

⁶ Arnott, R., and E. Kose, August 2014, What “Smart Beta” Means to Us, http://www.researchaffiliates.com/Our%20Ideas/Insights/Fundamentals/Pages/292_What_Smart_Beta_Means_to_Us.aspx

⁷ Amenc, N., F. Goltz, A. Lodh, S. Sivasubramanian, 2016, Diversified versus Concentrated Factor Indices, Journal of Portfolio Management, forthcoming.

only the evidence from asset pricing on additional risk factors, but also take into account the insights from portfolio theory (Markowitz (1952)⁸), 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.* 2014⁹). 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-adjusted returns to be improved relative to static exposure to a single factor, in particular when they are implemented as a dynamic strategy. Moreover, such strategies allow specific objectives to be taken into account in a given investment context such as risk targets in terms of absolute or relative risk. 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 realisations, and above 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 is 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 like 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 (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 with a 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 skilful 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 is essentially the result 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 indices.

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 emphasising their supposed alpha, which more often than not results from poor measurement (i.e. omission) of portfolio betas. While smart beta providers may be tempted to claim that their strategies deliver 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 and is well documented. The benefits of diversifying

⁸ Markowitz, H., 1952, Portfolio Selection, Journal of Finance, Vol. 7, No. 1, pp. 77-91

⁹ Amenc, N., F. Goltz, A. Lodh, and L. Martellini. 2014. Towards Smart Equity Factor Indices: Harvesting Risk Premia without Taking Unrewarded Risks. Journal of Portfolio Management 40(4): 106-122.

NOT ALL VALUE INDICES ARE EQUAL... SOME ARE SMART

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

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

With annual outperformance of 2.58% since the base date compared to MSCI World¹ and annual live outperformance of 1.90% compared to MSCI World Value,² the Scientific Beta Developed Value Diversified Multi-Strategy index is unquestionably a smart opportunity to invest in the Value factor.

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1 - The annualised relative return since the base date compared to MSCI World for the Scientific Beta Developed Value Diversified Multi-Strategy index as of December 31, 2015, is 2.58%. Analysis is based on daily total returns in USD from June 21, 2002 to December 31, 2015. The base date is December 21, 2002 for the Scientific Beta Developed Value Diversified Multi-Strategy index. MSCI World is used as the benchmark. All statistics are annualised.

2 - The annualised relative return since live date compared to MSCI World Value for the Scientific Beta Developed Value Diversified Multi-Strategy index as of December 31, 2015, is 1.90%. Analysis is based on daily total returns in USD from December 21, 2012 to December 31, 2015. The live date is December 21, 2012 for the Scientific Beta Developed Value Diversified Multi-Strategy index. MSCI World Value is used as the benchmark. All statistics are annualised.

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.

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 consensual insights and a vast amount of academic evidence.

Misconception 2: “Anything beats cap-weighted market indices”

Some have argued that the limitations of cap-weighted indices 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*”¹⁰. Consistent with this idea, it has been claimed¹¹ that “popular strategy indexes, when inverted, produce even better outperformance” and “the investment beliefs upon which many investment strategies are ostensibly based play little or no

‘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.’

role in their outperformance”.

Here we summarise results from Amenc *et al.* (2015)¹² who empirically assess the validity of such claims for a range of test portfolios. Exhibit 1 below 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 correspond to common offerings in the area of smart beta indices. The exhibit provides performance statistics relative to the cap-weighted reference index for both the original strategies and the inverted strategies.

The results displayed in the table show 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 3.94% 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

Exhibit 1: Performance of Smart Beta Strategies and their Upside-Down Strategies

All statistics are annualised and daily total returns from December 31, 1973 to December 31, 2013 are used for the analysis. The CRSP S&P 500 index is used as the cap-weighted benchmark. The table reproduces results for a selection of “Type 1” upside-down strategies from Exhibit 6 in Amenc *et al.* (2015)¹³

Stock Selection	Weighting Scheme	Ann Rel. Returns	Information Ratio
Mid Cap	Mid Cap Score Wtd	4.45%	0.60
Large Cap	Upside-down	-1.04%	-0.38
High Momentum	Momentum Score Wtd	1.96%	0.34
Low Momentum	Upside-down	-2.85%	-0.32
Low Volatility	Low Volatility Score Wtd	0.54%	0.09
High Volatility	Upside-down	-1.89%	-0.15
Value	Value Score Wtd	3.94%	0.66
Growth	Upside-down	-2.07%	-0.51
Low Investment	Low Inv Score Wtd	2.31%	0.52
High Investment	Upside-down	-1.80%	-0.38
High Profitability	High Prof Score Wtd	0.57%	0.12
Low Profitability	Upside-down	-0.58%	-0.08

¹⁰ Brightman, C. 2013. What Makes Alternative Beta Smart? Research Affiliates Publication. (September).

¹¹ Arnott, R. D., J. Hsu, V. Kalesnik and P. Tindall. 2013. The Surprising Alpha from Malkiel’s Monkey and Upside-Down Strategies. *Journal of Portfolio Management* 39(4): 91-105.

¹² Amenc, N., F. Goltz and A. Lodh, 2015, “Smart Beta is not Monkey Business”. *Journal of Index Investing*, forthcoming

¹³ Amenc, N., F. Goltz and A. Lodh, 2015, “Smart Beta is not Monkey Business”. *Journal of Index Investing*, forthcoming

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

‘Different smart beta strategies derive performance from different exposures to several factors that may go beyond size and value.’

There is a straightforward difference between the strategies analysed in Amenc *et al.* (2015) and the analysis that led others to the claim that anything beats cap-weighted indices¹⁴. In fact, one could easily be led to the conclusion that inverted strategies lead to similar outperformance as the original strategies when biasing the selection of strategies towards those that are similar to equal-weighting. Obviously, when inverting the weights of a strategy that is close to equal-weighting, one ends up with another strategy that is also close to equal-weighting, and thus the performance of the original and its

inverse will, unsurprisingly, look similar. The analysis in Amenc *et al.* (2015) avoids creating such a bias towards strategies that are close to equal-weighted by including a broad set of strategies tilting to different factors and using different weighting schemes.

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 growth, 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 deterministically improve performance, investors in smart beta strategies need to analyse the factor tilts and diversification mechanisms employed and identify which smart beta 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*”¹⁵ and 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)¹⁶ 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, 2012¹⁷; Clarke, de Silva and Thorley, 2013¹⁸; Asness, Moskowitz and Pedersen, 2013¹⁹; Asness, Frazzini and Pedersen, 2013²⁰).

Amenc, Goltz and Lodh (2015)²¹ 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 by the relevant factors. Possible explanations of this unexplained part of performance are that the improved diversification scheme allows value to be added beyond the explicit factor tilts, or that yet other additional factors, which are omitted from the factor model, are at work. However, while the findings in Amenc *et al.* (2015) are in line with this literature, they stand in stark contradiction to the claim that there is nothing beyond value and small-cap exposure in smart beta

¹⁴ Arnott, R. D., J. Hsu, V. Kalesnik and P. Tindall. 2013. The Surprising Alpha from Malkiel’s Monkey and Upside-Down Strategies. *Journal of Portfolio Management* 39(4): 91-105.

¹⁵ Arnott, R. D., J. Hsu, V. Kalesnik and P. Tindall. 2013. The Surprising Alpha from Malkiel’s Monkey and Upside-Down Strategies. *Journal of Portfolio Management* 39(4): 91-105.

¹⁶ Cited above

¹⁷ Leote de Carvalho, R., X. Lu and P. Moulin. 2012. Demystifying Equity Risk-Based Strategies: A Simple Alpha plus Beta Description. *Journal of Portfolio Management* 38(3): 56-70.

¹⁸ Clarke, R., H. de Silva and S. Thorley. 2013. Risk Parity, Maximum Diversification and Minimum Variance: An Analytic Perspective. *Journal of Portfolio Management* 39(3): 39-53.

¹⁹ Asness, C. S., T. J. Moskowitz and L. Pedersen. 2013. Value and Momentum Everywhere. *Journal of Finance* 68(3): 929-985.

²⁰ Asness, C. S., A. Frazzini, and L. Pedersen. 2013. Quality minus Junk. Working paper. AQR Capital Management.

²¹ Cited above

‘The term “smart beta” captures a vast variety of strategies with potentially very different properties.

strategies. Instead, these results suggest 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 cap-weighted indices – may introduce implicit factor

exposures (such as value and size, and potentially others). However, using alternative weighting schemes without providing any option to target factor exposures 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 control of such exposures, but instead rely on deconcentration with respect to cap-weighted indices, which naturally leads to the growth and large-cap bias of cap-weighted indices being avoided, without however controlling the direction in which the deviations from cap-weighting go, which leads to implicit factor exposures, but also potentially to other unmanaged and undocumented risks (e.g. 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 overweighting of financial stocks and underweighting of technology stocks) which may become a main driver of short-term performance without

necessarily providing an expected long-term reward (see Amenc *et al.* (2012²²)).

However, a Smart Beta 2.0 approach allows the issues with such uncontrolled implicit exposures to be addressed. In fact, Amenc *et al.* (2012²³) 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, it is straightforward to correct such tilts through 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.

Exhibit 2: Performance evaluation (alpha measurement) in a model with reversal factors

The results are based on daily total returns during the period from December 31, 1974 to December 31, 2014. The Market factor is the excess returns of the CRSP S&P-500 index over the risk-free rate. The yield on Secondary US Treasury Bills (3M) 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.

	SciBeta Long-Term USA Maximum Deconcentration	SciBeta Long-Term USA High-Momentum Maximum Deconcentration	SciBeta Long-Term USA Value Maximum Deconcentration	SciBeta Long-Term USA Mid-Cap Maximum Deconcentration
Ann. Rel. Returns	2.56%	3.46%	4.52%	4.33%
Regression on Market Factor and Reversal Factors				
Ann. Alpha	1.85%	2.68%	3.42%	3.06%
Mkt-RF	0.98	0.97	0.97	0.98
ST Reversal Factor	0.01	0.02	0.00	0.01
LT Reversal Factor	0.15	0.09	0.28	0.29
R-squared	94.71%	93.51%	90.22%	87.45%

²² Amenc, N., F. Goltz and S. Ye, 2012, Seeing through the Smoke Screen of Fundamental Indexers: What are the Issues with Alternative Equity Index Strategies? EDHEC Risk Institute, working paper

²³ Amenc, N., F. Goltz and A. Lodh, 2012, Choose Your Betas: Benchmarking Alternative Equity Index Strategies, Journal of Portfolio Management, Vol. 39, No. 1, pp. 88-111

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 that²⁴ “it is the rebalancing that provides the outperformance” of smart bet 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 (1993))²⁵. More recently, Plyakha, Uppal and Vilkov (2012)²⁶ 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)²⁷ recognises that there is no consensus in the literature on the existence of a positive rebalancing effect. Qian (2014)²⁸ provides an analysis suggesting that whether a rebalanced portfolio will outperform a buy-and-hold portfolio or underperform it depends on the behaviour of the component assets. 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 (1993²⁹, 2015³⁰) and Carhart (1997)³¹ do not include any rebalancing factor.

The paper by Cuthbertson et al (2015)³² 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 outperformance over the 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 estimates to aim at optimal 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 rebalancing 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 below. 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 indexation 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 this issue and empirical evidence showing that even fundamentals-based strategies do not have strong exposure to reversal effects, we refer to Amenc *et al.* (2015³³).

It is clear from these results that the different smart beta indices show

²⁴ The Maths Professor’s Smart-Alpha Sums Add Up. Financial Times. January 11, 2015

²⁵ Jegadeesh, N., and S. Titman. 1993. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *Journal of Finance*, vol. 48, no. 1 (March): 65-91.

²⁶ Plyakha, Y., R. Uppal, and G. Vilkov. 2012. Why Does An Equal-Weighted Portfolio Outperform Value- And Price-Weighted Portfolios? Working paper, EDHEC-Risk Institute.

²⁷ Cuthbertson, K., S. Hayley, N. Motson and D. Nitzsche, Diversification Returns, Rebalancing Returns and Volatility Pumping (January 14, 2015). Working Paper, available at SSRN

²⁸ Qian, E. E., A Mathematical and Empirical Analysis of Rebalancing Alpha (2014). *Journal of Portfolio Management*, Forthcoming.

²⁹ Fama, E. F., and K. R. French. Common Risk Factors in the Returns on Stocks and Bond, *Journal of Financial Economics* (1993)

³⁰ Fama, E. F., and K. R. French. A Five-Factor Asset Pricing Model, *Journal of Financial Economics* 116.1 (2015): 1-22.

³¹ Carhart, M. M. 1997. On Persistence in Mutual Fund Performance. *Journal of Finance*, vol. 52, no. 1: 57-82.

³² Cuthbertson, K., S. Hayley, N. Motson and D. Nitzsche, Diversification Returns, Rebalancing Returns and Volatility Pumping (January 14, 2015). Working Paper, available at SSRN.

³³ Amenc, N., F. Goltz, and A. Lodh, 2015, Is Smart Beta just Monkey Business? An Analysis of Factor Exposures, Upside-Down Strategies and Rebalancing Effects, EDHEC Risk Institute working paper, in particular see section 6.

high and significant alpha even when accounting for the reversal factors. Thus, the reversal factors do not fully capture the high average returns of 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 mechanics 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 and possible pitfalls. 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 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 which 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 oversimplification and calls for a detailed analysis of smart beta strategy performance taking into account the specific properties of the respective strategy.

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Enhancing LDI Solutions with Improved Equity Benchmarks

By Lionel Martellini, Professor of Finance, EDHEC Business School, Director, EDHEC-Risk Institute, Senior Scientific Advisor, ERI Scientific Beta and Vincent Milbau, Deputy Scientific Director at EDHEC Risk Institute

Liability-driven investing and beyond: fund separation versus fund interaction 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 optimally borrow the required amount 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.³⁴ 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 requires 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 generate 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 above-average liability hedging properties. For inflation-linked liabilities, we find that the use of a minimum variance equity benchmark based on a double-

³⁴ In addition to leverage constraints, the presence of uncertainty about parameter values, and in particular expected returns, also implies a departure from the theoretical framework, and the relative merits of various competing heuristic proxies for performance portfolios need to be empirically assessed as a function not only of their performance properties, but also of their hedging properties.

Table 1**Base Case Results on Liability-Friendly Portfolios**

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

	Selections				
	No Sel. (CW)	No Sel. (EW)	High Div Yield	High Correlation	Low Volatility
Panel A: Liability-friendliness indicators					
Tracking Error (%)	18.8	19.0	17.9 (***)	17.4 (***)	14.6 (***)
Volatility (%)	17.3	17.3	16.2 (***)	16.2 (***)	13 (***)
Correlation (%)	1.46	-0.8	1.88	7.58 (***)	7.73 (***)
Avg. Yearly Div. Yield	3.18	2.94	5.85	3.70	4.59
Panel B: Performance indicators					
Ann. Ret. (%)	10.9	13.3	13.8	14.6	13.2
Sharpe ratio	0.42 (***)	0.55	0.62 (*)	0.68 (**)	0.73 (***)
Turnover (%)	4.4	12.2	23.3	48.9	27.5
Cond. Ann. Ret.(%)	5.5	6.4	8.8	8.2	9.6
			Low Div Yield	Low Correlation	High Volatility
Panel C: Liability-friendliness indicators of opposite selections					
Tracking Error (%)			22.6 (***)	22.1 (**)	27.8 (***)
Volatility (%)			21 (***)	20.1 (**)	26.1 (**)
Correlation (%)			-1.8	-7.5 (***)	-6.7 (**)
Avg. Yearly Div. Yield			0.51	2.50	1.38
Panel D: Performance indicators of opposite selections					
Ann. Ret. (%)			11.3	12.4	10.7
Sharpe ratio			0.36 (**)	0.43 (*)	0.27 (***)
Turnover (%)			27.5	55.1	34.2
Cond. Ann. Ret.(%)			3.3	5.1	1.8

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 obtained with the use of 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 one is based on *cash-flow matching* capability: under this definition, liability hedging aims to find securities with dividend payments dividend payments 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 may choose instead to match the risk factor exposures of their assets with those of their liabilities. The objective pursued in this case is to immunise the funding ratio against variations in the risk factors that impact liabilities, and the success is measured in terms of tracking error with the liability proxy.

In this setting with a focus on risk factor matching, a stock will be said to be liability-friendly if the tracking error of the stock returns with respect

Table 2**Base Case Results on Liability-Friendly Portfolios**

	Equity Exposure	Volatility Funding Ratio for 40% Equity Allocation	Correlation with Liabilities	Iso Funding Ratio Volatility Equity Allocation
S&P 500	40.0%	7.0%	38.1%	
Min Variance Liability Friendly Portfolio	40.0%	5.2%	49.1%	54%

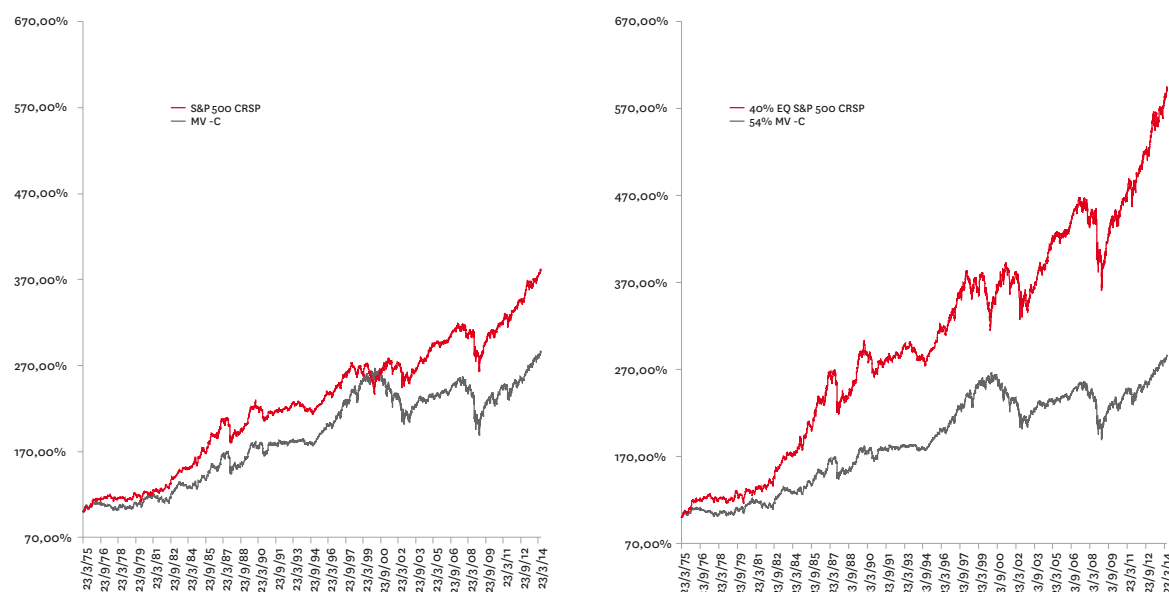
to the returns on the liability proxy is low. Given the decomposition of the tracking error into two components, one that is related to the portfolio volatility and one that is related to the portfolio correlation with the liability proxy, a low tracking error can be achieved either if the volatility of the stock is low and/or if the correlation between the stock and the liability proxy is high.

Using data from the CRSP database from 1975–2012, we construct portfolios with stocks originating from the S&P 500 universe. We cast the analysis at the individual stock level, as opposed to the sector level, given the expected presence of very substantial levels of cross-sectional dispersion in interest-rate-hedging benefits across individual stocks. The portfolios are rebalanced every year in March. In the analysis, the liability

proxy is computed as a constant maturity bond and its returns are computed using 15Y US treasury yields. The second step of the procedure establishes the weights that are assigned to each stock. We start by considering equal weights for all stocks (no selection EW), so as to assess the benefits of the selection stage, and we additionally provide the results for the cap-weighted portfolio of all stocks (no selection CW), which is the commonly used benchmark. In order to compare the relative performance of the portfolios, we compute the following out-of-sample indicators – the tracking error and correlation with respect to the liabilities, volatility, average dividend yield, Sharpe ratio and annual turnover (see Table 1).

From the comparison between Panel A and Panel C, we conclude that the various selection procedures indeed

deliver what they are designed for. In particular, the equally-weighted portfolio of the 20% of stocks with the lowest volatilities has a tracking error of 14.6% with respect to our liability proxy over the sample period, while the equally-weighted portfolio of the 20% of stocks with the highest volatilities is almost twice as large at 27.8%. This spectacular improvement in tracking error does not only emanate from lower portfolio volatility; it is also linked to a strong increase in correlation with the liabilities. Hence, the selection of low-volatility stocks generates a positive 7.7% correlation with the liability proxy, while a selection of high-volatility stocks generates a negative correlation of -6.7%. Intuitively, this improvement can be traced to the fact that low-volatility stocks, which tend to be low-dividend-

Figure 1: Historical Trajectories for the Funding Ratio

uncertainty stocks, are those that tend to be the closest approximations of fixed-income securities, and as a result, the best approximation of bond-like liabilities. In terms of correlations, the high-correlation selection ranks only second (although close to first), with a large turnover, suggesting that empirical correlations are highly unstable. We further observe that all selections increase the Sharpe ratio as well as the turnover, compared to both the EW and CW benchmarks, and the increased liability-friendliness of the portfolios is therefore not penalised by lower risk-adjusted performance.³⁵ We also confirm that the selection on dividend yields generates a statistically and economically-significant increase in this dimension with respect to the use of the standard S&P 500 index as a benchmark.

Measuring the impact on investor welfare

We also test a double-sort procedure, starting with the 200 highest dividend-yield (DY) stocks, selecting the 100 lowest-volatility stocks amongst 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 14.1%) 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 Table 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 dedicated equity benchmark with respect to the S&P 500 index, leads to an improvement in performance reaching 180 basis points annualised over the 1975-2014 sample period. This improvement can be decomposed into a contribution purely emanating from the increase in equity allocation assuming no impact on performance (57 basis points) and a contribution purely emanating from the improved performance of the equity benchmark assuming no increase in allocation (123 basis points).

In terms of historical trajectories, we plot the evolution of the funding ratio over the sample period in Figure 1, assuming an initial funding ratio normalised at 100%.

In the left plot of Figure 1, where the equity allocation is set to 40%, we note that the LDI strategy based on the improved liability-friendly portfolio strongly outperforms the LDI strategy based on the S&P 500 over the sample period. In the right plot of Figure 1, we observe that the outperformance is even more spectacular when the allocation to the improved equity benchmark is adjusted to generate the same volatility of the funding ratio as when investing 40%

in the S&P500 index.

Conclusion

We argue that LDI solutions can be enhanced by the design of performance-seeking equity benchmarks with improved liability-hedging properties. We show that liability-driven investors' welfare is not only increasing in terms of the Sharpe ratio of the performance-seeking portfolio and in the correlation of the liability-hedging portfolio with the liabilities, as suggested by the *fund separation theorem*, but it is also increasing in terms of the between the performance-seeking portfolio and the liabilities.

The practical implication of this *fund interaction theorem* is that investors, such as pension funds, will by and large benefit from improving hedging characteristics of their performance-seeking portfolio, unless this improvement is associated with an exceedingly large opportunity cost in terms of risk-adjusted performance.

We report evidence of the presence of a large amount of cross-sectional dispersion in liability-hedging characteristics of individual stocks within the S&P 500 universe. In particular, we find that high-dividend-yield stocks and low-volatility stocks are more bond-like than average, and therefore exhibit enhanced liability-hedging benefits. As a result, 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.

Within the S&P 500 universe, LDI strategies switching to such a liability-friendly equity benchmark starting from a 40% allocation to the S&P 500 index would benefit from an excess return of close to +1.8% per annum over the 1975-2014 period, without corresponding increase in funding ratio volatility.

³⁵ 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.

Harvesting Alternative Risk Premia

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

There is a growing interest amongst 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 Ang, Goetzmann and Schaefer (2009) analysis of the Norwegian Government Pension Fund Global), therefore implying 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, for example.

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 more generally (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 backfill bias. In what follows, we use EDHEC Alternative Indices, which aggregate monthly returns on competing hedge fund indices so as to improve the hedge fund indices' lack of representativeness and to mitigate the bias inherent to each database (see Amenc and Martellini (2002)). We consider the following thirteen categories: Convertible Arbitrage, CTA Global, Distressed Securities, Emerging Markets, Equity Market Neutral, Event Driven, Fixed Income Arbitrage, Global Macro, Long/Short Equity, Merger

Arbitrage, Relative Value, Short Selling and Fund of Funds.

The first step consists in defining a set of relevant risk factors and then finding suitable proxies. An overview of the 19 traditional and alternative risk factors considered in our empirical analysis is given in Table 1. We proxy traditional risk factors by total returns of liquid and investable equity, bond, commodity and currency indices. For alternative risk factors, we inter alia consider long/short proxies for the two most popular factors, namely value and momentum, for various asset classes, using data from Asness, Moskowitz and Pedersen (2013). A key difference between the traditional and alternative factors is that the latter cannot be regarded as directly investable, which implies that reported performance levels are likely to be overstated. Given the presence of performance biases in both hedge fund returns and alternative factor returns, we shall not focus on differences in average performance between hedge fund indices and their replicating portfolios, and instead focus on the quality of replication measured by in-sample and out-of-sample (adjusted) R-squared.

As a first step, we perform an in-sample linear regression for each hedge fund

‘A key difference between the traditional and alternative factors is that the latter cannot be regarded as directly investable.’

Table 1 – List of risk factors

	Risk Factors	Proxies	Source	CA	CTA	DS	EM	EMN	ED	FIA	GM	LSE	MA	RV	SS	FoF
Traditional Factors	Equity	S&P 500 TR	Bloomberg	Y	Y	Y		Y	Y		Y	Y	Y	Y	Y	Y
	Bond	Barclays US Treasury Bond Index	Datastream	Y	Y	Y			Y	Y	Y			Y		Y
	Credit	Barclays US Corporate Inv Grade Index	Datastream	Y		Y			Y	Y	Y			Y		Y
	Currency	US Dollar Index	Bloomberg				Y									
	Commodity	S&P GSCI TR	Bloomberg		Y											
	Emerging Market	MSCI EM TR	MSCI Web.			Y	Y		Y		Y			Y		Y
Alternative Factors	Multi-Class Value	Multi-Class Global VAL	AQR Web.			Y			Y		Y			Y		Y
	Multi-Class Mom.	Multi-Class Global MOM	AQR Web.			Y			Y		Y			Y		Y
	Equity Defensive	EQ Global BAB	AQR Web.	Y				Y				Y	Y		Y	
	Equity Size	EQ Global SMB	AQR Web.	Y				Y				Y	Y		Y	
	Equity Quality	EQ Global QMJ	AQR Web.	Y				Y				Y	Y		Y	
	Equity Value	EQ Global VAL	AQR Web.	Y				Y				Y	Y		Y	
	Equity Momen.	EQ Global MOM	AQR Web.	Y	Y			Y				Y	Y		Y	
	FI Momentum	FI Global MOM	AQR Web.		Y					Y						
	FI Value	FI Global VAL	AQR Web.							Y						
	FX Momentum	FX Global MOM	AQR Web.	Y												
	FX Value	FX Global VAL	AQR Web.													
	Commo Momen.	COM Global MOM	AQR Web.	Y												
	Commo Value	COM Global VAL	AQR Web.													

strategy's monthly returns against a set of K factors over the whole sample period ranging from January 1997 to October 2015. For each hedge fund strategy i we have: $r_{t,i} = \sum_{k=1}^K \beta_{i,k} f_{k,t} + e_{i,t}$, with $r_{t,i}$ being the monthly return of the hedge fund strategy at date t , $\beta_{i,k}$ the estimated OLS exposure of the monthly return on hedge fund strategy i to factor k , $f_{k,t}$ the monthly return at date t on factor k and $e_{i,t}$ the estimated specific risk in the monthly return of hedge fund index i at date t .

We estimate the explanatory power measured in terms of the regression adjusted-R-squared on the sample period in three distinct cases.

Case 1: Regression on an exhaustive set of factors (kitchen sink regression), i.e. the 19-factors set listed in Table 1.

Case 2: Regression on a subset of traditional factors only (5 factors: equity, bond, credit, commodity and currency).

Case 3: Regression on a bespoke subset

of a maximum of 8 economically-motivated traditional and alternative factors for each hedge fund strategy (see Table 1 for the selection of factors for each hedge fund strategy).

The obtained adjusted R-squared values, reported in Table 2, suggest that we can explain a substantial fraction of hedge fund strategy return variability with traditional and alternative factors, validating that a substantial part of hedge fund performance can be explained ex-post through their systematic risk exposures. The kitchen sink regression (case 1) confirms that more dynamic and/or less directional strategies such as CTA Global, Equity Market Neutral, Fixed Income Arbitrage and Merger Arbitrage strategies, with respective adjusted R-squared of 31%, 32%, 50% and 39%, are harder to replicate than more static and more directional strategies such as long/short equity or short selling, for which we obtain an adjusted R-squared of 81%.

The results we obtain also show the

improvement in the explanatory power when an economically-motivated subset of factors that includes alternative factors is considered (case 3) compared to a situation where the same subset of traditional factors is used for all strategies (case 2). For example, adjusted R-squared increases from 25% to 50% for Global Macro strategy and from 52% to 80% for Emerging Market strategy.

In a second step, we perform an out-of-sample hedge fund return replication exercise using the bespoke subset of factors for each strategy (case 3). The objective of this analysis is to assess whether one can capture the dynamic allocation of hedge fund strategies by explicitly allowing the betas to vary over time in a statistical model.

The out-of-sample window considered is January 1999 – October 2015, which allows us to build a “24-month rolling-window” linear clone for each strategy. For each hedge fund strategy i we have: $r_{t,i} = \sum_{k=1}^K \beta_{i,k,t} f_{k,t} + e_{i,t}$.

Here $r_{t,i}$ is the monthly return of the hedge fund strategy i at date t , $\beta_{i,k,t}$ the

Table 2 – In-sample adjusted R-squared for empirical data

	CA	CTA	DS	EM	EMN	ED	FIA	GM	LSE	MA	RV	SS	FoF
Case 1: 19 Factors	54	28	52	80	16	63	28	50	71	31	56	73	68
Case 2: Traditional Factors (except Emerging Market)	49	12	42	52	-2	55	35	25	64	22	55	60	46
Case 3: Economic Factors (see Table 1)	56	31	71	85	32	77	50	58	81	39	70	81	77

estimated OLS exposure of the monthly return on hedge fund strategy i to factor k on the rolling period $[t-24\text{months}; t-1]$, $f_{k,t}$ the monthly return at date t on factor k and $e_{i,t}$ the estimated specific risk in the monthly excess return of hedge fund i at date t .

The hedge fund clone monthly return for strategy i is: $r_{t,i}^{\text{clone}} = \sum_{k=1}^K \beta_{i,k,t} f_{k,t} + (1 - \sum_{k=1}^K \beta_{i,k,t}) r_{ft}$.

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 3-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:

$$\begin{aligned} \beta_t &= \beta_{t-1} + \eta_t \quad (\text{transition equation}) \\ r_t &= \beta_t' F_t + \varepsilon_t \quad (\text{measurement equation}) \end{aligned}$$

where β_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 . η_t and ε_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: $r_{t,i}^{\text{clone}} = \sum_{k=1}^K \beta_{i,k,t|t-1} f_{k,t} + (1 - \sum_{k=1}^K \beta_{i,k,t|t-1}) r_{ft}$.

The substantial decrease between in-sample (see Table 2) and out-of-sample (see Table 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 Table 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

Table 3 – Out-of-sample adjusted R-squared and annualised root mean squared error for empirical data

	HF clone Rolling-Window Out-of-Sample Adjusted R-Squared (%)	HF clone Kalman Filter Out-of-Sample Adjusted R-Squared (%)	HF clone Rolling-Window RMSE (%)	HF clone Kalman Filter RMSE (%)
CA	38	47	4.8	4.4
CTA	-13	8	8.5	7.6
DS	29	-1	4.9	5.8
EM	81	77	4.6	5.0
EMN	-4	-8	2.8	2.8
ED	48	20	4.0	5.0
FIA	21	31	3.3	3.1
GM	26	-23	4.0	5.0
LSE	57	58	4.6	4.5
MA	-4	20	3.2	2.8
RV	46	49	3.0	2.9
SS	74	71	7.8	8.3
FoF	60	37	3.4	4.7

‘Risk parity strategies applied to alternative risk factors could be a better alternative than hedge fund replication.’

‘Can suitably designed mechanical trading strategies in a number of investable factors provide a cost-efficient way for investors to harvest traditional but also alternative beta exposures?’

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 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 computing their Sharpe ratios.

The first two rows of Table 4 gives 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 set of factors and the methodologies used. Our results also 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. In the end, the relevant question may not be "is it feasible to design accurate hedge fund clones with similar returns and lower fees?", for which the answer appears to be a clear negative, but instead "can suitably designed mechanical trading strategies in a number of investable factors provide a cost-efficient way for investors to harvest traditional but also alternative beta exposures?". With respect to the second question, there are reasons to believe that such low-cost alternatives to hedge funds may prove a fruitful area of investigation for asset managers and asset owners.

The research from which this article was drawn was produced as part of the Lyxor Asset Management "Risk Allocation Solutions" research chair at EDHEC-Risk Institute.

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Providing Meaningful Retirement Investment Solutions

By 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 2000-2003 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 pension to defined-contribution pension schemes is taking place across the world.³⁶ 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-based market-centred 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 *aspirational* consumption goals, with possible additional goals including healthcare, old age care and/or bequest goals.

Some dramatic changes with respect to

³⁶ As an example of this evolution, the number of Fortune 500 companies offering traditional DB plans to new hires fell from 51% in 1998 to 7% in 2013 (Towers Watson. 2014. Retirement in Transition for the Fortune 500: 1998 to 2013. Insider Report (September). Available at: <https://www.towerswatson.com/en/Insights/Newsletters/Americas/Insider/2014/retirement-in-transition-for-the-fortune-500-1998-to-2013>).

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‘The need for the investment industry to start providing both institutions and individuals with meaningful retirement, investment solutions has become more obvious than ever.’

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 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 investors' problems are broadly summarised in terms of their liabilities.

In a nutshell, GBI includes two distinct elements (see Deguest *et al.* (2015) for a detailed analysis). On the one hand, it involves the disaggregation of investor preferences into a hierarchical list of goals, with a key distinction between *essential* and *aspirational* goals, and the mapping of groups according to hedging portfolios that possess corresponding risk characteristics. On the other hand it involves efficient dynamic allocation to these dedicated hedging portfolios and a common performance-seeking portfolio. In this sense, the GBI approach is formally consistent with the fund separation theorems that serve as founding pillars for dynamic asset pricing theory, 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 funds and, more recently, exchange-traded. 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 and personalisation 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 risk-aversion parameter, then the aforementioned fund separation theorems state that

all investors need to hold a *specific* combination of two *common* funds, one risky fund used for risk premia harvesting, and one safe (money market) fund. In reality different investors have different goals, as discussed above, and the suitable extension of the fund separation theorems implies that if the performance-seeking building block can be the same for all investors, the safe building block(s), which are known as goal-hedging portfolio(s) and are the exact counterparts in individual money management of liability-hedging portfolios in institutional money management, should be (mass) customised. Besides, the allocation to the safe rather than risky building blocks should also be engineered so as to secure investors' *essential* goals (e.g., *minimum* levels of replacement income) while generating a relatively high probability to achieve their *aspirational* goals (e.g., *target* levels of replacement income).

That mass customisation is the key challenge that our industry is facing was recognised long ago, but it is only recently that we have developed the actual capacity to provide such dedicated investment solutions to individuals. The point was very explicitly made by Merton (2003): “It is, of course, not new to say that optimal investment policy should not be “one size fits all”. In current practice, however, there is much more uniformity in advice than is necessary with existing financial thinking and technology. That is, investment managers and advisors have a much richer set of tools available to them than they traditionally use for clients. (...) I see this issue as a tough engineering problem, not one of new science. We know how to approach it in principle (...) but actually doing it is the challenge.”

Paraphrasing Robert Merton, I would like to emphasise that designing

meaningful retirement solutions does not indeed require a *new science*. All the required ingredients are perfectly well-understood in the context of dynamic asset pricing theory (see for example Duffie (2001)), namely (1) a safe (goal-hedging) portfolio that should be truly safe; (2) a risky (performance-seeking) portfolio that should be well rewarded; and (3) an allocation to the risky portfolio that (3.i) reacts to changes in market conditions and (3.ii) secures investors' essential goals while generating a high probability of reaching aspirational goals.

On the other hand, scalability constraints required to address mass-customisation do pose a *tough engineering challenge*, since it is hardly feasible to launch a customised dynamic allocation strategy for each individual investor. There are in fact two distinct dimensions of scalability, scalability with respect to the *cross-sectional dimension* (designing a dynamic strategy that can approximately accommodate the needs of different investors entering at the same point in time) and scalability with respect to the *time-series dimension* (designing a dynamic strategy that can approximately accommodate the needs of different investors entering at different points in time). The good news is that financial engineering can be used to meet these challenges (see Martellini and Milhau (2016) for a detailed analysis).

In closing, let me state that the magnitude of what is happening should not be under-estimated. I do believe that that our industry is truly about to experience somewhat of an industrial revolution within the next 5 to 10 years. We currently are at the confluence of historically powerful forces. On the one hand, liquid and transparent access to risk premia-harvesting portfolios is now feasible with smart factor indices, which are cost-efficient and scalable alternatives to active managers. On the other hand, distribution costs are bound to go down from their stratospheric levels as the trend towards *disintermediation* accelerating, particularly through the development of FinTech and robo-advisor initiatives, which are putting the old business model under strong pressure, and forcing wealth management firms to entirely rethink the value that

they are bringing to their clients.

In the profound soul-searching process that is currently underway 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.

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Do Infrastructure Firms Differ from Other Firms?

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

In a new paper drawn from the work of the EDHECinfra/Meridiam/Campbell Lutyens research chair on 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?

Are infrastructure firms different?

Our motivation springs from what we have called the known “infrastructure investment narrative” (Blanc-Brude 2013), according to which investors in infrastructure can look forward to low correlation of returns with the business cycle (hence potentially better diversification), as well as lower sensitivity to economic shocks (implying better drawdown protection).

Empirical evidence for or against such hypotheses has so far been very limited. This study is a first iteration in a series of research papers using a new, global database of infrastructure investment data, and that aim to measure the relative financial performance of such investments through the creation of fully-fledged benchmarks or reference portfolios.

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.³⁷

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 the Companies House.³⁸ 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 United Kingdom, 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 United Kingdom by independent agencies such as Ofwat or Ofgem.

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

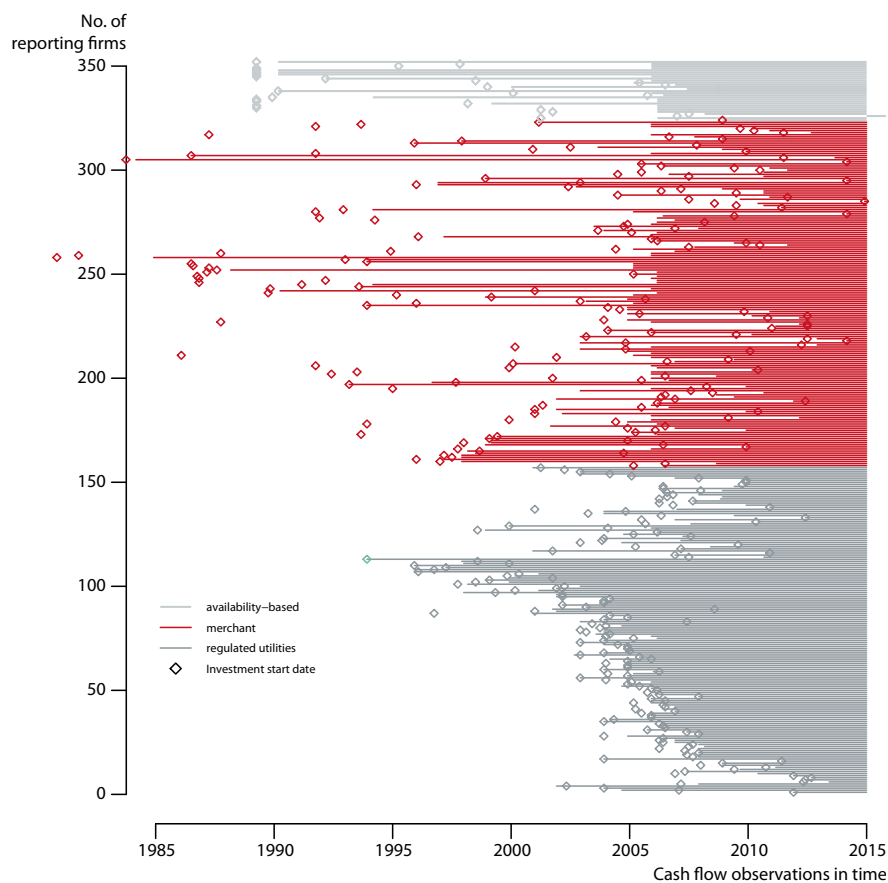
We focus on UK data because they are the largest, longest and most coherent set of infrastructure cash flow data available at this time, with the added advantage of corresponding to a single currency and

³⁷ See Blanc-Brude and Hasan (2015) for a theoretical approach to discount rate estimation in private infrastructure assets.

³⁸ The UK Company Register

Figure 1: Number and time frame of reporting firms in the EDHEC*infra* database. Each line represents a time series of cash flow data

Scope and breadth of the infrastructure cash flow dataset



regulatory environment, thus limiting the need to control for these dimensions in the analysis. Starting from UK infrastructure firms, we can also build robust control groups of non-infrastructure firms, with which to compare the data.

Controlling for the different aspects of firm behaviour

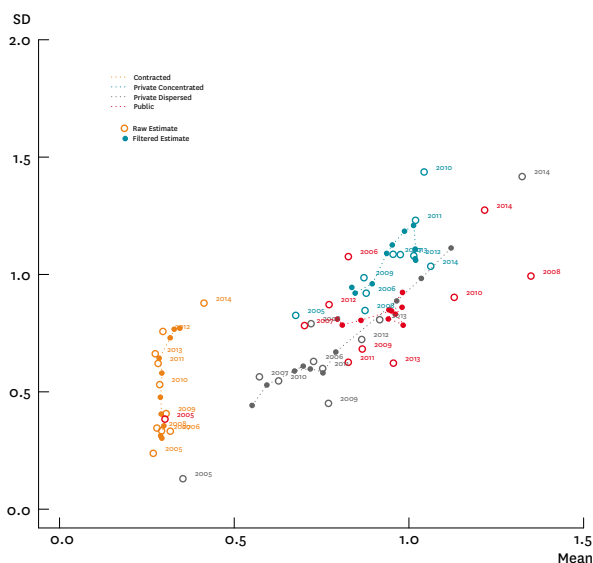
Our sample of several hundred infrastructure firms is compared with a “matched sample” of non-infrastructure UK firms, both private and listed.

Indeed, while public market data has sometimes been used as a proxy of private infrastructure firms, recent research has shown that private firms exhibit significant differences in terms of size, capital structure and dividend policy: private firms tend to be smaller than listed firms, they exhibit higher leverage, making their profits more sensitive to fluctuations in performance, they have different dividend payout policies than listed firms and are less inclined to smooth their dividends in the presence of profit shocks. Moreover, differences in ownership structure in private firms are also shown to explain how much they differ from public firms (see Brav 2009; Michaely and Roberts 2012 for a detailed study).

To control for the effect of ownership structure and corporate governance on the behaviour of infrastructure firms, we build three control groups for each one of our infrastructure-firm-type: private firms with concentrated ownership, private firms with dispersed ownership

Figure 2: Estimates of the mean and variance parameters of the unit revenues and profits in calendar time for Contracted Infrastructure and matched control firms

Revenue/Assets Ratio Trajectories in Calendar Year



Profits/Average Assets Ratio Trajectories in Calendar Year

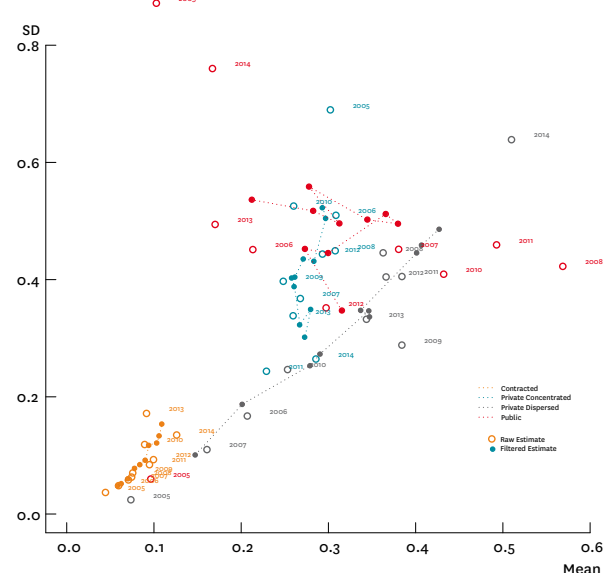
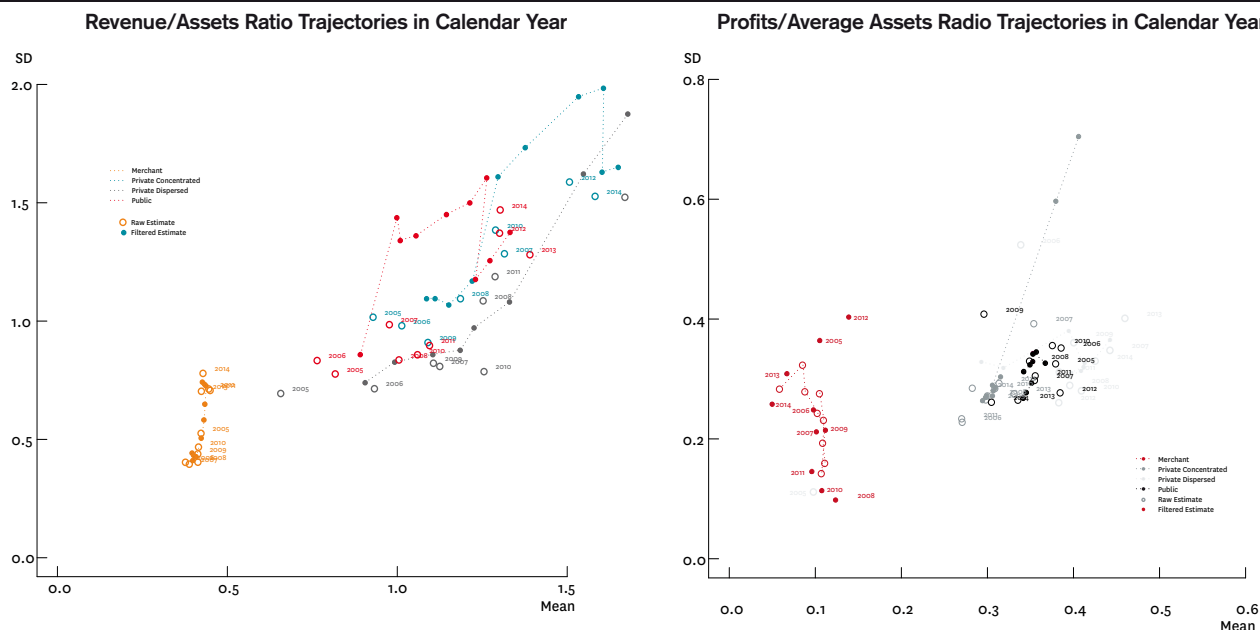


Figure 3: Estimates of the mean and variance parameters of the unit revenues and profits in calendar time for Merchant Infrastructure and matched control firms



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 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.

1. 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;
2. 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;
3. Infrastructure firms exhibit a very **dynamic lifecycle** compared to control groups, with unit revenues

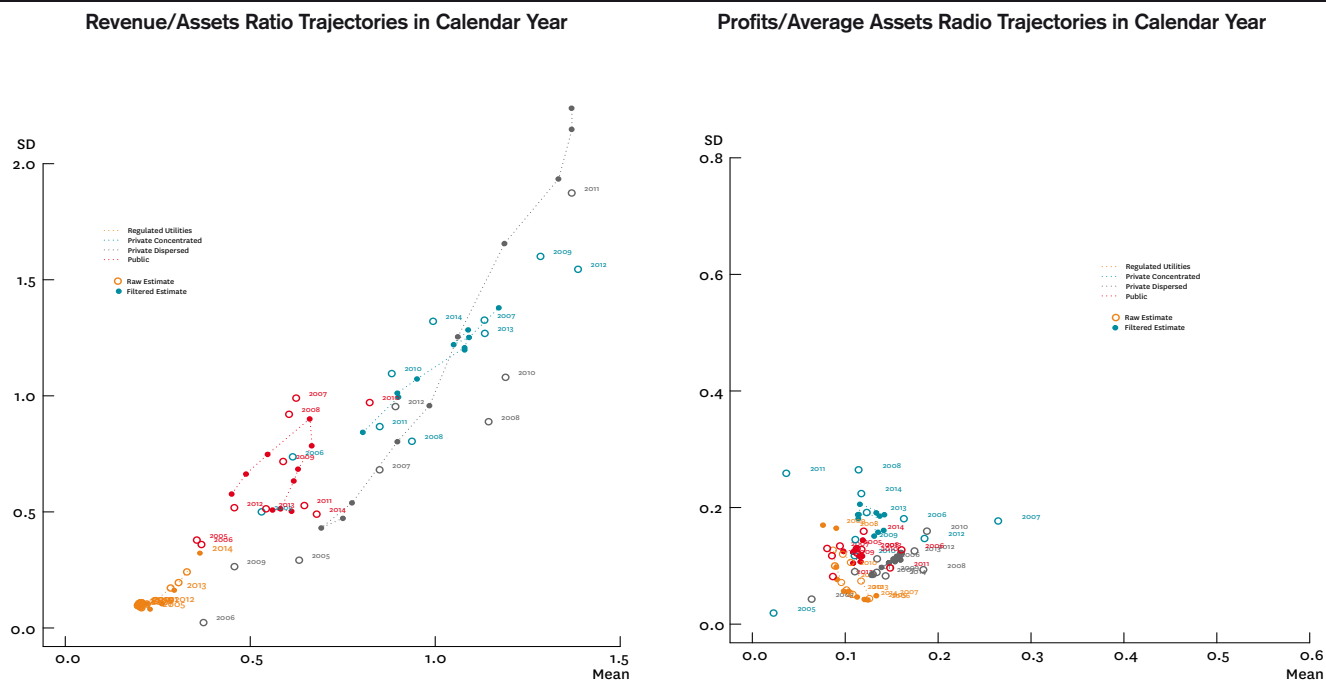
and profits evolving by an order of magnitude over the investment cycle;

4. **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 merchant infrastructure 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 and private firms with concentrated ownership, and the effect is much larger for non-infrastructure firms. Larger firms, including infrastructure firms, also tend to have lower profits, but the effect is again much more muted than for control

‘Infrastructure firms exhibit a truly unique, business model.’

Figure 4: Estimates of the mean and variance parameters of the unit revenues and profits in calendar time for Regulated Infrastructure and matched control firms



groups and it is not significant for merchant infrastructure.

5. **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.
6. 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%.
7. 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 successfully be matched to private non-infrastructure firms.

We find that the equity payout behaviour of infrastructure firms is very different from that of other firms: infrastructure firms pay off more often and in significantly higher proportions of their revenues than other firms once the lifecycle of the firm is taken into account.

We conclude that infrastructure firms have significantly lower volatility of revenues and profits and pay a much higher proportion of their revenues much more frequently to their owners, independent of the business cycle.

Another significant result is that each of the three types of infrastructure firms that we define (according to a typology we first described in Blanc-Brude (2013)) corresponds to a unique business model as well, albeit more alike amongst themselves when compared to the rest of the corporate universe, Contracted, Merchant and Regulated infrastructure firms have their own coherent cash flow dynamic.

The research from which this article was drawn was produced as part of the Meridiam Infrastructure/Campbell Lutyens “Infrastructure Equity Investment Management and Benchmarking” research chair at EDHECinfra.

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Private Infrastructure Project Debt: Cash Flow Dynamics

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

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 or DSCRs, which measure the amount of cash available to make the current period's debt service in private infrastructure debt.

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:

1. An unambiguous definition of the

- point of hard default (default of payment), i.e. $DSCR=1$, and
2. An equally unambiguous definition of key technical default covenants i.e. $DSCR=1.x$, while both types of default events create significant embedded options for creditors following a credit event.
 3. 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.
 4. DSCR dynamics can also be combined with future debt service to compute the expected value and volatility of the firm's future free 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.

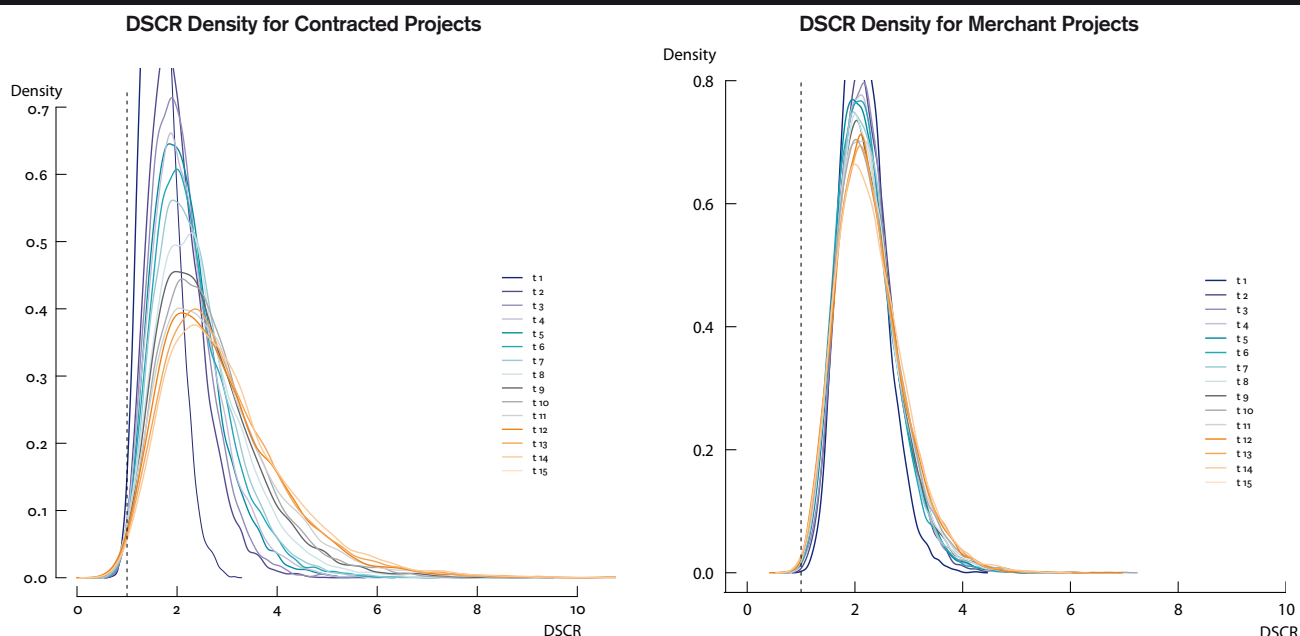
In particular, individual infrastructure investments can exhibit significant "path dependency" and investors cannot necessarily take for granted the notion that they are exposed to the "median infrastructure project."

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

'DSCRs can play a pivotal role in the modelling of credit risk in fixed income infrastructure investments.'

Figure 1: DSCR densities for contracted and merchant families

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

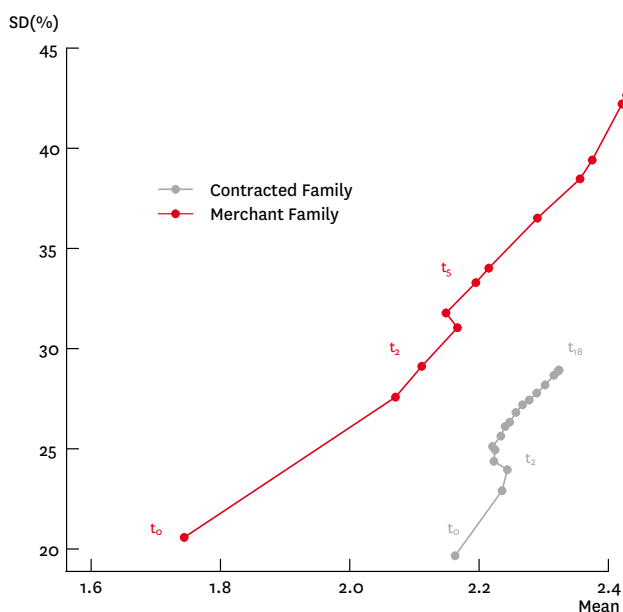
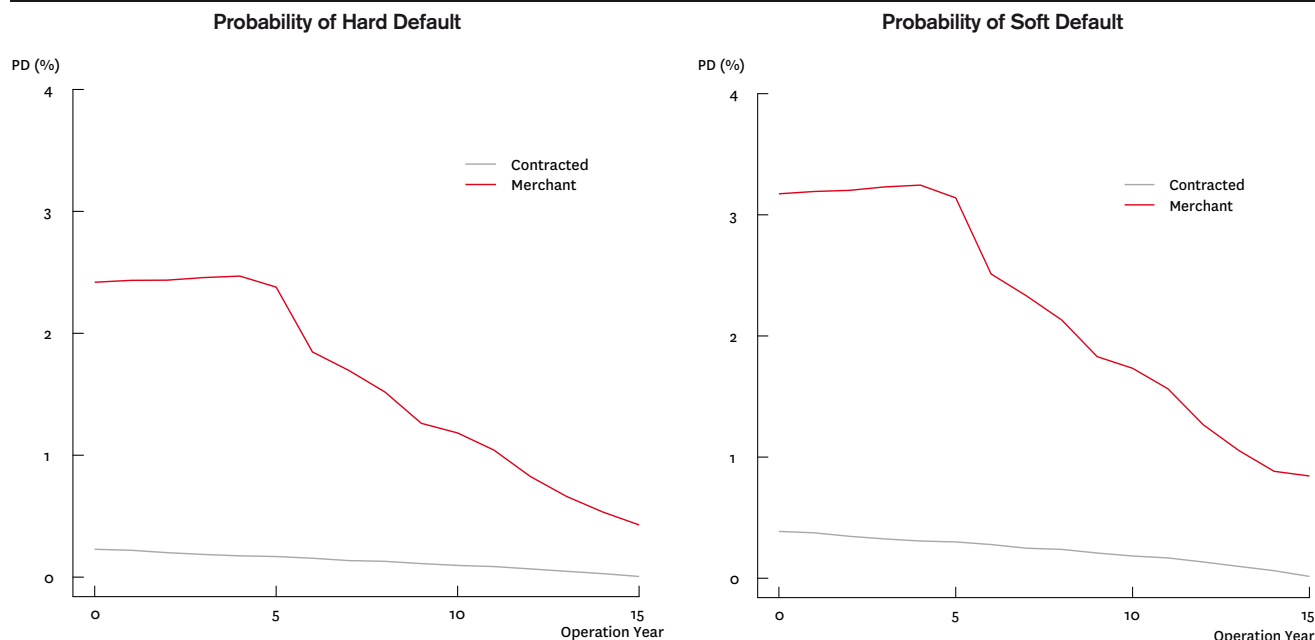
Figure 2: DSCR trajectories in the state (m, σ) plane, for both families

Figure 3: Probabilities of hard and soft defaults for contracted and merchant families; computed as the probabilities of DSCR_t falling below 1.0 and 1.05, respectively



defined in Blanc-Brude, Hasan, and Ismail (2014).

Dividing infrastructure investments into groups defined by their “business model”

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

This distinction was informed by the casual observation that the financial structure of infrastructure project finance vehicles is often such that it requires, at the onset, either a rising or a flat “base case” DSCR profile.

A rising base case DSCR profile then implies increasing volatility of DSCR_t. That is, creditors would demand a higher DSCR in the future to protect themselves against rising expected volatility of the cash flows available for debt service (CFADS). Such projects would also have longer “tails” and exhibit between 70% and 80% of initial senior leverage. We argued that such structuring decisions signalled infrastructure projects that were exposed to commercial risks, such as a power plants selling electricity at market prices, and referred to these projects as Merchant infrastructure.

Conversely, we argued that the decision to structure a project while requiring a lower and flatter base case DSCR profile implied the expectation of lower and constant conditional volatility of cash flows. We observed that projects with little to no market risk are financed

with such a flat DSCR base case and also have shorter tails and a higher level of senior leverage, usually around 90%. Examples of these projects include social infrastructure projects, such as schools or hospitals that receive a fixed payment from the public sector, or energy projects that benefit from a long-term “take-or-pay” purchase agreement. We called these projects *Contracted* infrastructure.

In our research, we endeavour to determine statistically whether **realised DSCR dynamics** fall into categories determined by the distinctions made above between Contracted and Merchant infrastructure, as well as exogenous conditions at the time of financing and when the data is observed. We then use our results to design a model of DSCR dynamics.

The largest sample of DSCR data available for research to date

Our dataset of realised DSCRs is built using data manually collected and verified from the audited statements of accounts of several hundred project companies, as well as DSCR data reported by private contributors.

We hand-collected 15 years of realised DSCR data for more than 200 projects in Europe and the United States covering our two broad categories of projects (those receiving contracted income and those exposed to merchant or commercial risks), in seven sectors, from the early 1990s to 2015. Our initial analysis of the data reveals some important points that confirm our intuition: the average credit

risk profile of infrastructure projects can be usefully captured by categorising instruments into broad groups or families of underlying “business models.”

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 DSCRs in the cross section are much less affected by macro-variables or the business cycle than merchant projects.

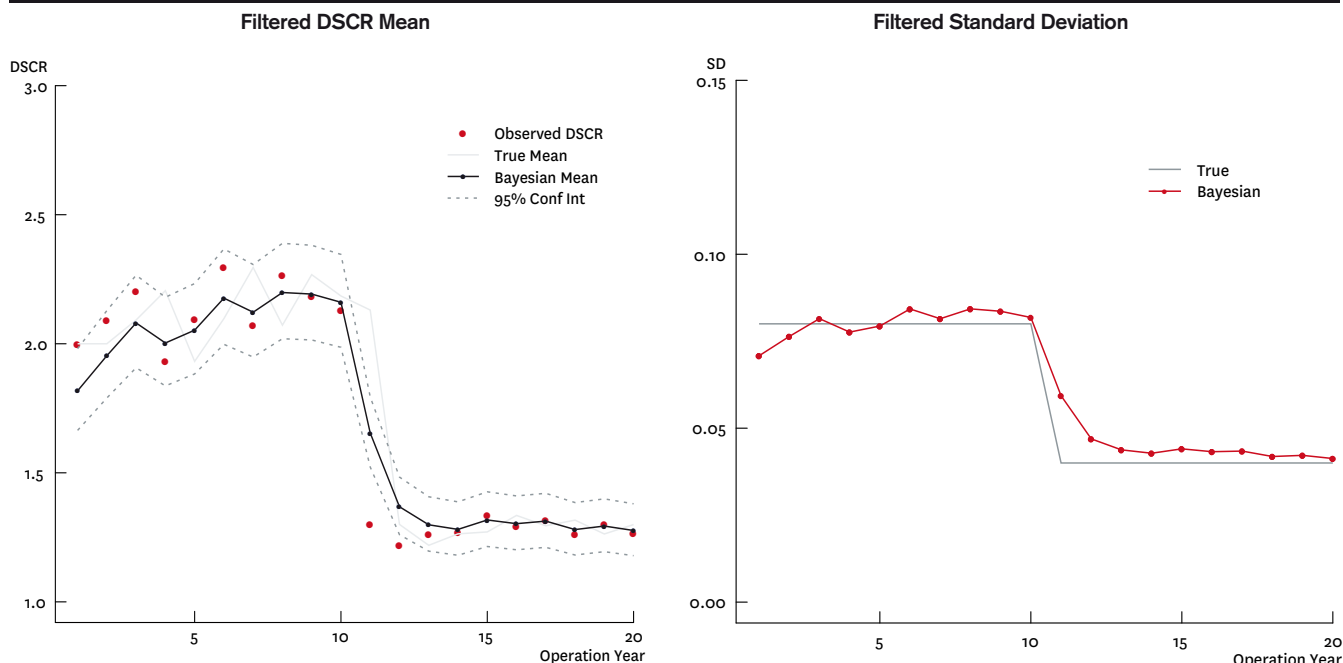
We confirm our hypothesis that the DSCR profile of an infrastructure project is strongly related to the firm’s total business risk, and show that more highly leveraged projects achieve lower levels of realised DSCR volatility, i.e. in project finance high leverage signals low asset risk as initially argued by Esty (2003).

That said, while descriptive statistics and linear regression models provide some insights about the determinants of the DSCRs, they fail to capture DSCR dynamics in full. Indeed, we find that the DSCR profiles of individual projects and families of 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_t is serially correlated and can change profile during the investment

Figure 4: Filtered DSCR quantiles and standard deviation for a single project experiencing a negative shock

lifecycle of infrastructure projects, the ex post trajectory of individual projects could in principle correspond to any combination of high/low expected value $E(DSCR_t)$ and high/low volatility $\sigma^2 DSCR_t$. The DSCR of populations of projects would equally reflect the weighted trajectory of their constituents in a $DSCR_t$ 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 research, we apply such approaches to estimate the position of a given infrastructure project in a mean/volatility DSCR plane at a given point in time, and to predict its position, its DSCR mean and variance “coordinates” so to speak, in the following 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 break up points in 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) in which it is indeed an autoregressive lognormal process, a default state (D) defined by a threshold corresponding to $DSCR_t=1$ in which the DSCR process stops until it emerges from default; and a safe state (S),

corresponding to high realised values 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 $DSCR_t=1$, it enters the default state, which it may or may not leave after a number of periods. In this state, creditors can take over the firm and optimise the value of exercising this option depending on the size of their exit costs and of restructuring costs. They may decide to waive the event of default or engage in negotiations with the project sponsor 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 (2014) for a formal model).

Hence, the firm may transit out of the default state (into the risky state) with some probability (say, π_{dr}) at the next period, or stay in this state and again

‘The ability to predict cash flows and their volatility is instrumental in the implementation of the private infrastructure debt valuation model.’

transit out of default at the next period, etc.

In this state, the DSCR process effectively stops (in most cases, there is 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, from a senior creditor 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 safe state at each point in the future, with some probability (say, π_{dr}).

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 \overline{DSCR} . From this state, it may either stay in the *risky* state at the next period, 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

of our DSCR sample, the data follows a lognormal process, the parameters of which (position and scale) have to be estimated.

Formally, this set-up amounts to a relatively simple model of conditional state transition probabilities, which can be set in terms of a series of binomial draws and calibrated using Bayesian inference given some prior knowledge (e.g. we know from credit rating studies that projects tend to stay in default for 2.3 years) 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 of switching state at each point in time are 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 other two states, i.e. 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 *DSCR*, 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 ($DSCR_t = 1.x$) 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

*‘DSCR profiles...
are highly non-
linear, auto-
regressive and
heteroskedastic
(variance is not
constant).’*

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_0 .

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 $DSCR_t$ are updated accordingly. Likewise, initial estimates of the volatility of $DSCR_t$ 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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1 - The average annualised relative return since the base date compared to the cap-weighted benchmark for Scientific Beta Multi-Beta Multi-Strategy Quality indices for various regions as of January 22, 2016 is 3.46%. The base date is June 21, 2002. Analysis is based on daily total returns (with dividends reinvested) from June 21, 2002 to January 22, 2016 for the Developed, USA, Extended USA, Eurozone, UK, Extended Developed Europe, Japan, Developed Asia Pacific ex Japan, Developed ex USA, Developed ex UK, and Developed Europe ex UK regions. The benchmark used is a cap-weighted portfolio of all stocks in the respective Scientific Beta universes. All statistics are annualised. Source: scientificbeta.com.

