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Research for Institutional Money Management

EDHEC-RISK Institute

INTRODUCTION

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

It is a great pleasure to introduce the latest edition of the EDHEC-Risk Institute "Research for Institutional Money Management" supplement in cooperation with Pensions & Investments.

Our first article, drawn from research conducted within the "Advanced Modelling for Alternative Investments" research chair at EDHEC-Risk Institute supported by Newedge, examines the convergence between mainstream and alternative asset management. By looking at the regulatory context established with the creation of UCITS funds in Europe, we have the interesting attribute of being able to test the impact of regulation on the performance of hedge funds. We find that UCITS hedge funds underperform non-UCITS hedge funds on a total and risk-adjusted basis. However, UCITS hedge funds have more favorable liquidity terms and when we compare liquidity matched groups of UCITS hedge funds and non-UCITS hedge funds, we find that UCITS hedge funds generate similar performance. We therefore uncovered an important liquidity-performance trade-off in the sample of UCITS hedge funds. We feel that even though the research was conducted with European data, the "natural" experience that enables the performances and risks of highly-regulated hedge funds and those that are less so to be compared is of interest to North American professionals.

Defined-benefit pension funds' liabilities are often inflation-linked, which motivates the search for asset classes with good inflation-hedging properties. However, what matters for investors with inflation-linked liabilities is not the inflation-hedging ability of an asset class, but its inflation-linked liability-hedging ability. The distinction between inflation hedging and liability hedging is all the more important in that, for maturities exceeding one year, the contribution of interest rate risk to short-term liability variance is much larger than that of inflation risk. In our article, based on research carried out as part of the Ontario Teachers' Pension Plan research chair at EDHEC-Risk Institute on "Advanced Investment Solutions for Liability Hedging for Inflation Risk", we show in a quantitative way that interest rate risk matters more than inflation risk from a short-term perspective, and review various approaches to interest rate risk hedging and inflation hedging.

In an article on infrastructure investment, drawn from a research chair at EDHEC-Risk Institute with Meridiam and Campbell-Lutyens, we provide an eight-step roadmap for making long-term infrastructure investment relevant to institutional investors. A major effort remains to be made by investors, managers, regulators and academics to contribute to the development of relevant investment solutions in infrastructure assets, including state-of-the-art methodologies and the definition of the minimum data required to implement them and answer benchmarking and asset allocation questions seriously. Market players must also embrace the standardized and transparent reporting of underlying cash flow data for these benchmarks to become a reality.

Given that there is so much choice in the area of alternative forms of equity indices, a natural question that arises for investors is which index to select. A good smart beta index is one that diversifies away the specific risks and manages the exposure to equity risk factors. Our article shows how to construct smart (well-diversified) factor indices and the benefits gained from diversifying across them – the multi smart factor approach.

We also examine the performance of smart beta equity indices using long-term (40-year) data. Most smart beta indices are marketed on the basis of outperformance, but usually their back-tests are conducted over a limited time period. Critics of smart beta often question the robustness of these strategies over the long term, but in our long-term analysis all diversification strategies deliver higher returns than the cap-weighted reference index, with annualized outperformance of more than 2.3%. Moreover, all of the diversification strategy indices exhibit better risk-adjusted performance.

We then examine the robustness of the outperformance of smart beta (alternative-weighted) equity strategies. Assuming that certain market conditions may influence the capacity of a given weighting scheme to provide outperformance over cap-weighted reference indices, it is crucial for investors to assess the risk of underperformance as well as the conditional performance profile of any smart beta strategy so as to gain a better picture of the robustness of the potential outperformance of a strategy.

We would again like to thank our friends at P&I for their help in producing this "Research for Institutional Money Management" supplement and wish you all a very pleasant and informative read.

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www.edhec-risk.com

CONTRIBUTORS

Antoine Thabault
antoine.thabault@scientificbeta.com

Ashish Lodh
ashish.lodh@scientificbeta.com

Felix Goltz
felix.goltz@edhec-risk.com

Frédéric Blanc-Brude
frederic.blanc-brude@edhec.edu

Juha Joenväärä
jjoenv@paju.oulu.fi

Lionel Martellini
lionel.martellini@edhec-risk.com

Noël Amenc
noel.amenc@edhec-risk.com

Robert Kosowski
robert.kosowski@edhec-risk.com

Vincent Milhau
vincent.milhau@edhec-risk.com

PORTFOLIO MANAGEMENT

An Analysis of the Convergence between Mainstream and Alternative Asset Management

Robert Kosowski
Affiliate Professor, EDHEC-Risk Institute and Associate Professor in the Finance Group of Imperial College Business School

Juha Joenväärä
Assistant Professor
University of Oulu

Over the last few years institutional investors' traditional portfolios have failed to meet their objectives in terms of risk and performance. Investors have thus demonstrated a growing interest in new forms of diversification and especially in investment vehicles offering better protection during extreme market conditions. This has naturally led them to increasingly consider hedge funds as part of their investment universe, but also to search for access to sophisticated risk management techniques within the regulated and transparent world of mutual fund products.

While this convergence of mainstream long-only asset management and alternative hedge funds has been much talked about for some years, it has not been realized on any significant scale until recently. Two main forces are currently accelerating the trend. The first of these forces, from the supply side, was the amendment of the UCITS framework in Europe, which allowed mainstream fund managers to supply regulated forms of hedge fund-type products to their traditional customer base, while also permitting hedge funds to reach out to the same customers. The UCITS context enables the impact of regulation on the performance of hedge funds to be tested

The second of these forces, from the demand side, is the increased interest of private but also, and more importantly, institutional investors in novel, more sophisticated forms of mutual fund investing strategies, and which has led to the rapid development of regulated products implementing absolute return strategies and 130/30 strategies. Such products are often perceived as an entry door to the alternative industry, or a middle ground between complex and opaque hedge fund strategies and unsophisticated mutual fund strategies without any substantial added value in terms of risk management. It is important to note that the convergence goes in both directions, as an increasing number of hedge fund managers are now offering regulated products as well.

Research objectives

In recent research[1] produced as part of the Newedge research chair at EDHEC-Risk Institute on "Advanced Modelling for Alternative Investments" we had two objectives. First, our research provides an academic analysis of the main techniques that are currently used by hedge fund managers and that could be transported to the mutual fund and alternative UCITS space in a straightforward manner so as to provide better forms of risk management in a regulated environment.

Alternative investment fund managers are increasingly deciding to implement alternative strategies through traditional investment vehicles such as mutual funds in order to access assets from retail and institutional investors that, for various reasons (such as investment mandates, for example), cannot invest through less regulated structures. Packaging hedge fund strategies in a traditional format is not straightforward and it raises a lot of challenges for the managers as well as for the brand of the regulatory format. An important question is to know whether structuring hedge fund strategies through mutual funds will compromise these strategies and provide the same level of returns, considering the constraints under mutual fund regulations such as investment restrictions, liquidity requirements, operational requirements and risk management. We therefore carefully examine how dynamic trading and derivatives strategies can be transported to the mutual fund space.

Our second objective is to examine the convergence between the mainstream and the alternative asset management industry by studying UCITS hedge funds (UHFs)[2] and non-UCITS hedge funds (HFs).[3]

Literature review and our contribution

Our paper is related to three streams of the literature. First, it is related to recent work on 'hedged mutual funds' in the US as well as studies on alternatives UCITS. Agarwal, Boyson and Naik (2009) study 'hedged mutual funds' which they define as mutual funds regulated by the SEC but employing hedge fund-like strategies. They study 49 hedged mutual funds and find that despite using similar trading strategies, hedged mutual funds underperform hedge funds. The authors attribute this finding to hedge funds' lighter regulation and better incentives. In their sample, hedged mutual funds outperform traditional mutual funds. Their analysis suggests that this superior performance is driven by managers with experience implementing hedge fund strategies. The authors use the CRSP Survivorship-Bias-Free mutual fund database and include all hedged mutual funds which appear in the Morningstar and Lipper databases that classify funds as hedged mutual funds based on several criteria other than the investment objectives reported in Morningstar and Lipper. In contrast to hedged mutual funds studied by Agarwal, Boyson and Naik (2009), alternative UCITS funds have no restrictions on incentive structures. Our research is also related to that of Koski and Pontiff (1999) and Almazan et al. (2004) who investigate the differences in performance of mutual funds that use derivatives and mutual funds that do not.

In one of the more recent studies of UCITS funds, Darolles (2011) examines alternative UCITS funds. Similar to Agarwal, Boyson and Naik (2009) he finds that hedge fund experience counts when managing alternative UCITS funds. Darolles (2011) studies 450 alternative UCITS funds in the Morningstar database on 450 alternative UCITS funds from June 2004 to May 2011 and compares them to 2,782 hedge funds. Furthermore, the study finds that that the regulatory constraints come with a cost in terms of performance, but that this cost depends on the hedge fund's investment objective. This result is in line with the study by Stefanini et al. (2010), who find that, on average, alternative UCITS funds underperform by 3.5%. Stefanini et al. (2010) employ a tracking error approach to compare performance of offshore traditional hedge fund and the corresponding onshore UCITS version. Other studies examine UCITS using smaller databases. Tuchschmid et al. (2010) examine 191 alternative UCITS funds using the Alix UCITS Alternative Index database. Pascalau (2011) uses a sample of 66 USD share class UCITS from the BarclayHedge database. Tuchschmid et al. (2010) and Pascalau (2011) both use the Fung and Hsieh (2004) model to calculate risk-adjusted return performance.

Our study builds on and extends the above papers in three main ways. First, by using one of the most comprehensive aggregate UHF and HF databases constructed to date, we increase the data sample significantly both in the time series (with data ending 2012) and the cross-section. The advantage of using an aggregate database is that given the relatively small number of UHFs compared to HFs we are more likely to capture the full universe of exciting UCTS funds. Second, we use a significantly larger number of cross-sectional variables that allows us to capture not only aspects of the incentives faced by managers (performance fees, high watermarks, etc.) but also liquidity conditions (redemption, notice and lockup periods) which have not been studied in the above studies.

Third, our paper is related to the literature that documents cross-sectional performance differences among hedge funds. This literature shows that funds with greater managerial incentives (e.g. Agarwal, Daniel, and Naik (2009), Aggarwal and Jorion (2010)), strict share restrictions (e.g., Aragon (2007)), and less binding capacity constraints (e.g., Teo (2010)), on average, outperform their peers on a risk-adjusted basis. On the relationship between liquidity and hedge fund performance, Aragon (2007) argues that share restrictions allow hedge funds to manage illiquid assets and earn an illiquidity premium. Teo (2011) examines hedge funds that grant favorable redemption terms to investors. He finds that hedge funds that are exposed to liquidity risk, but not shielded by strict share restrictions, underperform during times of financial distress due to costly capital outflows. Joenväärä, Kosowski and Tolonen (2012, hereafter JKT (2012)) aggregate five commercially-available hedge fund databases and show that the stylized facts about hedge fund performance and certain fund characteristics are sensitive to the database used.

We build on this work by using information about funds' regulatory structure which allows us to impose testable restrictions on the relationship between liquidity and UHFs' performance and risk.

UCITS and non-UCITS hedge funds

The amendments of the UCITS framework referred to as UCITS III and IV allow mainstream fund managers to supply regulated forms of hedge fund-type products to their traditional customer base, while also permitting hedge funds to reach out to the same customers.[4] Alternative UCITS or UCITS hedge funds are funds that follow a hedge fund type strategy aiming to generate absolute return or absolute performance. They are, in other words, simply UCITS that take advantage of certain investment techniques allowed by the UCITS regulations which enable them to pursue strategies that were previously more common in the alternative investment sector in particular, the hedge fund sector.

Based on regulatory requirements that apply to UCITS, we economically motivate a range of hypotheses regarding differences in AuM growth, performance and risk between UHFs and HFs and empirically test them using one of the most comprehensive hedge fund databases constructed to date. We examine differences between UHFs and HFs based on a range of

[1] *Joenväärä, J. and R. Kosowski. February 2013. An Analysis of the Convergence between Mainstream and Alternative Asset Management. EDHEC-Risk Publication produced as part of the Newedge research chair on "Advanced Modelling for Alternative Investments."*
[2] *UCITS III compliant hedge fund strategies are sometimes referred to as or Newcits or 'absolute' UCITS.*
[3] *The Undertakings for Collective Investment in Transferable Securities, Directives 2001/107/EC and 2001/108/EC (or "UCITS") are a set of European Union Directives that are designed to allow collective investment schemes to operate freely throughout the EU on the basis of a single authorization from one member state.*
[4] *See, for example, http://www.hedgefundintelligence.com/UCITS.*

cross-sectional fund features such as investment objectives and other fund characteristics including compensation and redemption structures. Regulatory requirements that apply to UCITS imply that UHFs impose less binding share restrictions than HFs. Hence, UHF investors can exploit performance persistence, if any, more easily than HF investors. Our research sheds light on the convergence of mainstream and alternative investment management as well as drivers of performance and risk for different types of UCITS funds. This study is timely since UCITS funds, and in particular the so-called retailization of complex products and the use of total return swaps, recently attracted the attention of regulators.[5]

UCITS funds differ from hedge funds in several ways which leads to testable hypotheses about differences in their performance and risk. First, the requirement of a (i) separate risk management function in UCITS funds as well as (ii) leverage limits and (iii) VaR (Value-at-Risk) limits leads to our first hypothesis that the risk of UHFs is lower than that of HFs. Measuring risk is a complex issue and therefore we apply a range of different risk metrics to capture tail-risk in addition to volatility (Patton (2009). Second, UCITS funds face restrictions regarding the use of derivatives. This leads to two further hypotheses. Our second hypothesis is that restrictions in the use of derivatives reduce option-like payoff profiles and non-normal returns in UHF return distributions. Our third hypothesis is that reduced flexibility in the use of derivatives makes UHF returns less counter-cyclical than those of HFs. A fourth hypothesis is that the investment objective is crucial and that the extent to which UCITS restrictions affect risk and performance depends on the investment objective of the fund. We therefore carry out our hypotheses tests for all funds as well as by investment objective to distinguish, for example, Long/Short Equity funds, Global Macro funds as well as Event Driven funds. Previous studies of UHFs have typically focused on a smaller set of investment objectives (Darolles (2011)). Our fifth hypothesis is related to the fact that different countries have implemented the UCITS directive in different ways, which implies that geography and in particular domicile matters for UHFs.

One of the main strengths of our research is that we examine the relationship between performance and risk of HFs and UHFs and a range of economically important fund characteristics related to fund manager incentives and fund liquidity which have not been previously examined in the context of UHFs. Liquidity is linked to fund performance in at least two important ways. First, liquidity, in terms of less binding redemption restrictions for UHFs investors, may allow them exploit performance persistence. On the one hand, JKT (2012) show that HF performance may hypothetically persist but investors' ability to exploit it is limited by strict share restrictions. Hence, the UHF universe provides an interesting setting to test whether performance persists and whether it can be exploited in practice.

On the other hand, Teo (2011) provides evidence that capital outflows can be costly if HFs are exposed to liquidity risk. This suggests that liquidity may be harmful in certain circumstances. Thus, it is interesting to study the role of share restrictions and liquidity risk for UHFs. Moreover, in terms of the time-series and number of funds in our data, our research is to our knowledge one of the most comprehensive analyses of the performance and risks of HFs and UHFs. Previous studies have typically analyzed UHFs in isolation without comparing them to the HF universe or they have examined at most 460 UHFs and less than 2,800 HFs. First, we carry out a comprehensive aggregation process to construct an aggregate HF dataset that consists of more than 24,000 unique hedge funds that report at least 12 return observations. This database consists of active and inactive or defunct funds. This group of funds represents our HF control group. The number of hedge funds in our database is close to that reported by the UBS' proprietary AIS database consisting of about 20,000 hedge funds and 45,000 share classes[6], while the PerTrac 2010 hedge fund database study finds that the hedge fund industry contains about 23,600 funds. Therefore, we believe that our aggregate database containing the union of five major databases is close to the true unobservable population of hedge funds.

Second, by merging data on UCITS funds from the EurekaHedge, BarclayHedge, and HFR databases on UCITS hedge funds we also construct an aggregate database on UHFs. In our study we thus carry out a comprehensive analysis and comparison of both UHFs and HFs. Hedge fund databases are also non-overlapping – we find that almost 70% of funds in our consolidated database report only to one of the used major databases. JKT (2012) recently documented that data biases are different between hedge fund databases, thus affecting stylized facts about performance and risk of HFs. This suggests that merging several databases will provide us with a more accurate view of the aggregate size of the UCITS hedge fund universe.

We document stylized facts about hedge fund performance, data biases, and fund-specific characteristics explaining cross-sectional differences in UHF and HF performance. To understand why the performance results differ between UHFs and HFs, we start by highlighting how the total return and AuM time-series differ on a value and equal-weight basis between UHFs and HFs. We then move to differences in fees and risk-adjusted performance and study how Sharpe ratios, the Fung and Hsieh (2004) seven-factor model alphas and risk exposures differ between HFs and UHFs.

Finally, we examine the cross-sectional relationship between fund characteristics and hedge fund performance. The existing literature on HFs has documented that managerial incentives, share restrictions and capacity constraints are associated with cross-sectional differences in hedge fund performance. Using portfolio sorts and the Fama and MacBeth (1973) regressions, JKT (2012) demonstrate that smaller and younger funds, and funds with greater capital flows deliver better future returns than their peers. This conclusion is in line with the previous literature (e.g., Teo, (2010) and Aggarwal and Jorion (2010)). In contrast to the existing literature, JKT (2012) find, however, that fund characteristics related to managerial discretion or illiquidity do not consistently explain hedge fund cross-sectional returns. In fact, they find very little evidence that share restrictions in the form of lockup, notice and redemption periods are related to higher risk-adjusted returns when they control for the role of other characteristics in multivariate regression. Given regulatory requirements on the liquidity of UHFs it is therefore of particular interest to study the relationship between UHF performance and fund liquidity.

In our empirical results, we find that UHFs underperform HFs on a total and risk-adjusted basis. However, UHFs have more favorable liquidity terms and when we compare liquidity matched groups of UHFs and HFs, we find that UHFs generate similar performance. Thus we uncovered an important liquidity-performance trade-off in the sample of UHFs.

Our results also show that HFs have generally lower volatility and tail risk than UHFs, which is consistent with hurdles to the transportation of risk management techniques discussed. Finally we find important domicile effects related to firm and fund performance. ~

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

The purpose of the chair is to expand the frontiers in alternative investment modeling techniques by enhancing the understanding of the dynamic and non-linear relationship between alternative investment returns and the returns on underlying fundamental systematic factors, and analyzing the implications for managing portfolios that include alternative investments.

The full version of the research is available on the EDHEC-Risk Institute website at the following address: http://www.edhec-risk.com/multistyle_multiclass/Newedge_Research_Chair

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[5] *See, for example, ESMA's guidelines on ETFs and other UCITS issues, available at http://www.esma.europa.eu/system/files/2012-44_0.pdf.*

[6] *See, Güner, Rachev, Edelman, and Fabozzi (2010). The AIS database includes funds that UBS allocated capital to, but that do not report to commercial databases.*

PORTFOLIO MANAGEMENT

Hedging Inflation-Linked Pension Liabilities without Inflation-Linked Instruments[7]

Vincent Milhau
Deputy Scientific Director
EDHEC-Risk Institute

Lionel Martellini
Professor of Finance EDHEC Business School
Scientific Director, EDHEC-Risk Institute

Inflation risk versus inflation-linked liability risk
Liabilities of defined-benefit (DB) pension funds often include a clause of indexation on consumer prices or wage levels. The presence of uncertainty in future prices and wages raises the problem of finding appropriate hedging instruments for these risks. Price inflation hedging is relatively straightforward if cash instruments, such as inflation-linked bonds, or OTC derivatives, such as inflation swaps, are available. However, the inflation-linked bonds market may lack sufficient capacity to meet the demand from institutional investors, and derivatives-based solutions are subject to counterparty risk. Besides, there is no financial security perfectly indexed to wages. As a consequence, pension funds are unlikely to find instruments that allow for perfect cash-flow matching, which motivates the search for asset classes with good inflation-hedging properties.

It is important to recognize, however, that what matters for investors endowed with inflation-linked liabilities is not the inflation-hedging ability of an asset class, but instead its inflation-linked liability-hedging ability. The two concepts are equivalent at the date liabilities are paid, but not at previous dates; indeed, liability value, as the present value of future payments, strongly depends on the discount rate, especially when the payment is to take place in a remote future. Thus, an asset class (e.g., commodities or infrastructure) may be found to be a good hedge for inflation-linked cash-flows at the final date, but have low correlation with liability value before the maturity date because of poor interest rate hedging properties. This is a concern, because low short-term correlation leads to high short-term volatility in the funding ratio, which makes it more difficult to respect the short-term funding constraints imposed by many regulations and otherwise scrutinized by stakeholders of the pension plan (trustees, CFO of the sponsor company, etc.).

The distinction between inflation hedging and liability hedging is all the more important in that, for maturities exceeding one year, the contribution of interest rate risk to short-term liability variance is much larger than that of inflation risk for realistic parameter values. In this context, nominal bonds appear to be the best substitute for inflation-linked bonds in liability-hedging portfolios. On the other hand, while inflation risk is not quantitatively important in the short run, its importance grows as the payment date approaches, and it eventually becomes the sole source of uncertainty at this very date. Nominal bonds are therefore poorly suited to hedging liability risk at the liability maturity date: the correlation of a nominal bond payoff and inflation-linked liabilities is zero at horizon.

In what follows, we show in a quantitative way that interest rate risk matters more than inflation risk from a short-term perspective. We then review various approaches to interest rate risk hedging and inflation hedging.

Relative importance of interest rate and inflation risks in liabilities

We first provide a quantitative breakdown of liability risk into interest rate and inflation risks. For simplicity, let us assume away the presence of longevity risk, and let us represent liabilities in a single inflation-indexed payment. The fair liability value is thus given by the price of an inflation-indexed zero-coupon bond. Within the context of a formal model for interest rate and inflation, Martellini and Milhau (2013a) (henceforth MM13a) show that the variance of liabilities over a very short horizon h (e.g., one day or one week) is given by:

$$\sigma_L^2 \approx \left[D^2\sigma_r^2 + \sigma_\Phi^2 - 2D\sigma_r\sigma_\Phi\rho_{r\Phi}\right]h \qquad (1)$$

where σ_r and σ_Φ are the annual volatilities of the short-term rate and the price index, $\rho_{r\Phi}$ is the correlation of these two processes and D is the liability duration. Given the low volatility of the price index, which falls in general between 1% and 2% per year, it is easy to guess from Equation (1) that for long durations, interest rate will account for most of liability variance.

It is difficult in Equation (1) to disentangle the respective contributions of interest rate and inflation risks, due to the presence of the correlation term. In order to have a quantitative assessment of the contribution of interest rate risk, MM13a compute the absolute value of the short-term correlation between nominal bonds and liabilities. As shown in Exhibit 1, the correlation is larger than 98% for maturities longer than five years, but falls to 75.62% for the one-year maturity. The analysis can be repeated with other assets, such as a broad stock index (here, the S&P 500 index) or a broad commodity index (here, the Goldman Sachs Commodity Index).

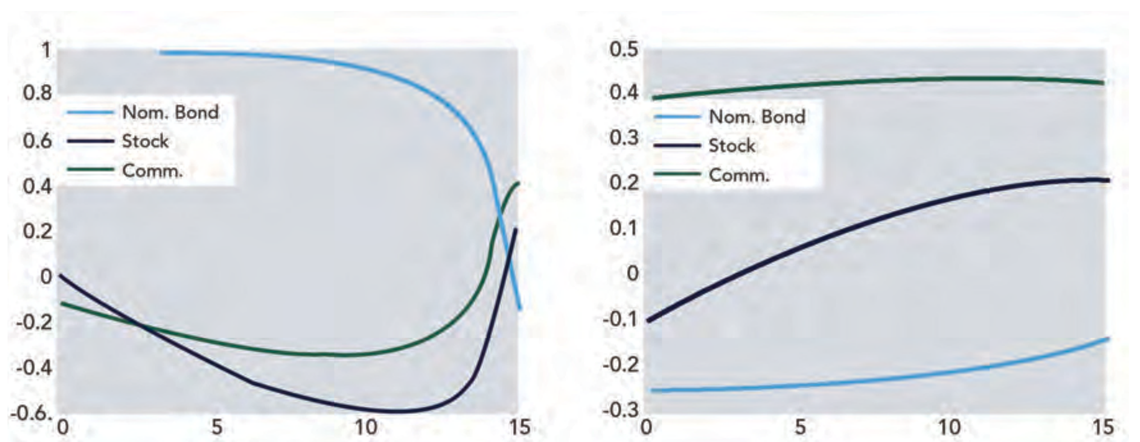
EXHIBIT 1

Absolute value of the short-term correlation between asset classes and liabilities, in percent.
We consider different liability maturities and different asset classes. Parameter values have been obtained by calibrating a model to US market data over 1961-2011 (see MM13a for details).

Liability maturity (years)	15	10	5	1
Asset class				
10-year nominal bond	99.73	99.54	98.63	75.62
Broad stock index	0.43	2.96	0.53	8.28
Broad commodity index	10.14	9.30	6.63	14.23

EXHIBIT 2

Term structures of correlations between asset classes and liabilities (left panel) and between asset classes and realized inflation (right panel).
Liabilities are paid in 15 years, and the both the nominal and the inflation-linked bond have a constant maturity of 10 years. Parameter values are the same as in Exhibit 1.



[7] This research has benefited from the support of Ontario Teachers' Pension Plan in the context of the research chair "Advanced Investment Solutions for Liability Hedging for Inflation Risk".

It is important to recognize, however, that what matters for investors endowed with inflation-linked liabilities is not the inflation-hedging ability of an asset class, but instead its inflation-linked liability-hedging ability.

Clearly, neither the stock nor commodities prove effective in reducing the volatility of the funding ratio. This may be explained by the absence of a stable interest rate risk exposure for these assets.

The picture, however, changes dramatically if one looks at correlations over longer horizons, as in the left panel of Exhibit 2. First, a simple visual comparison of the two panels shows that correlations with liabilities and correlations with inflation are very different, except at the fifteen-year horizon, which corresponds to the payment date. Moreover, nominal bonds are not as effective in terms of liability hedging at horizons close to liability maturity as they are at short horizons: their correlation with liabilities decreases rapidly as the payment date approaches, and the commodity index appears to be the best liability hedge at this horizon. It is because it has the highest correlation with inflation at the fifteen-year horizon (right panel of Exhibit 2).

These findings illustrate the presence of a structural conflict between short-term and long-term liability hedging. Nominal bonds are excellent hedging instruments in the short run thanks to their interest rate exposure, but have poor (in fact, zero) liability-hedging properties at maturity when inflation-hedging remains the only source of uncertainty, which favors asset classes such as commodities with reasonably attractive inflation-hedging benefits.

Challenges for inflation and interest rate hedging in liabilities

Eventually, two distinct sources of risk are to be hedged: inflation risk and interest rate risk. In this section, we discuss some challenges associated with these questions.

Since it may be difficult for institutional investors to rely on inflation-linked bonds or derivative instruments to hedge against inflation risk, a number of empirical works have assessed the inflation-hedging properties of traditional and alternative asset classes. The results of these studies have been mixed. A general finding, which is also apparent from Exhibit 2 above, is that a broad stock index, such as the S&P 500 index, has better inflation-hedging properties in the long run than in the short run. This is an attractive property, given that pension funds precisely have long horizons. Within the equity market, Ang et al. (2012) show that it is possible to find stocks or sectors with more attractive inflation-hedging benefits than the broad index, because inflation betas are widely dispersed across stocks and sectors. For instance, the stocks with the best hedging benefits are often found in the oil and gas and the technology sectors, while financial stocks are overrepresented in the low inflation beta class. These findings can be related to economic intuitions, such as differences in the pricing power of firms in periods of rising inflation. But unfortunately, it is difficult to exploit the knowledge of stocks with past highest inflation betas to construct inflation-hedging portfolios, because betas happen to be highly unstable over time. Similarly, a constant-maturity nominal bond has negative correlation with inflation in the short run, and this correlation increases with the horizon (see Hoevenaars et al. (2008) and Exhibit 2). This can be explained by the positive relationship between nominal rates and expected inflation, which is itself positively linked to realized inflation. In the short run, bond returns covary negatively with the interest rate, hence with inflation, but in long periods of rising inflation, they benefit from the roll-over effect at increasing interest rates. When it comes to alternative asset classes, commodities display good inflation-hedging properties at all horizons (see Hoevenaars et al. (2008), Amenc et al. (2009), and, again, Exhibit 2).

However, as noted above, finding asset classes that are highly correlated with inflation does not address the problem of reducing the short-term volatility in the funding ratio, which mainly depends on their interest rate hedging properties. In order to manage interest rate risk, investing in nominal bonds is the most obvious solution. On the other hand, it should be noted that while they provide a quasi perfect hedge against nominal interest rate risk, nominal bonds are not necessarily good at hedging real interest rate risk, which is the relevant source of risk in inflation-indexed liabilities. More specifically, Fabozzi and Xu (2012) show that nominal bonds have non-zero duration with respect to expected inflation, while this duration is zero for indexed bonds: as a consequence, in periods of high increases in expected inflation, nominal bonds tend to perform poorly, while liabilities are little affected, to the extent that the real rate stays constant. This mismatch in expected inflation exposure between nominal bonds and inflation-linked liabilities is a potentially important source of risk for pension funds using nominal bonds as proxies for inflation-linked bonds in their liability-hedging portfolios.

Moreover, nominal sovereign bonds are by construction discounted at the sovereign rate, but liabilities are not necessarily valued at this rate. This is particularly the case under the international accounting standards SFAS 87.44 and IAS 19.78, which recommend the use of the corporate AA rate as a discount rate. In this context, investment grade corporate bonds may be more effective in hedging liability fluctuations than sovereign bonds. As another advantage, corporate bonds are expected to deliver better performance over the long term than their sovereign counterparts, because their return includes a credit risk premium. Martellini and Milhau (2013b) study the welfare gains achieved by substituting corporate bonds for sovereign bonds, and show that these gains are precisely higher when liabilities are valued at the AA rate than at the risk-free rate. On the other hand, nominal corporate bonds are also exposed to changes in expected inflation, while real liabilities are not. ~

CONCLUSION

In conclusion, the intuition that DB pension funds should invest in assets that are positively correlated with inflation in order to hedge against inflation risk appears to be incomplete at best. While only inflation risk matters at the date the inflation-indexed pension payment is made, interest rate risk is a much more important component of liability risk in the short run. Nominal bonds are the natural candidates to hedge against that risk, but they suffer from at least two shortcomings. Firstly, they do not provide any hedging benefit at the payment date, and secondly, they are perfectly correlated with changes in nominal rates but not changes in real rates. In these conditions, only inflation-linked bonds achieve the ideal target of a perfect liability matching at all horizons.

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This chair analyzes the design of novel forms of inflation-hedging portfolios that do not solely rely on inflation-linked securities but instead involve substantial investment in traditional asset classes.

Overall these novel forms of inflation-hedging solutions should be engineered to generate higher expected performance for a given inflation hedging level, which in turn will allow for a decrease in the cost of inflation hedging.

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PORTFOLIO MANAGEMENT

A Roadmap to Make Long-Term Infrastructure Investment Relevant to Institutional Investors

Frédéric Blanc-Brude
Research Director
EDHEC Risk Institute—Asia

Long-term investing and the demand for monitoring

The intertemporal monitoring demand

Long-term investment can be defined in terms of investor horizon or instrument characteristics. Long-term investors intend to hold securities over multiple trading periods, possibly until maturity. Long-term instruments are characterized by the unavailability of a fair instantaneous payoff[8]: trades are infrequent and investing requires patience. Infrastructure equity investment requires both long-term investors and instruments.

Long-term equity investment leads to an increase in the demand for monitoring on the part of investors. Two motives determine this intertemporal monitoring demand: first, the opportunity to improve firm performance as an active shareholder with a long-term horizon; and second, the necessity to measure and benchmark the performance of infrequently traded assets.

Recent research on the impact of longer investment horizons on monitoring demand with frequently traded assets allows the two motives to be isolated. In public markets, investors have a choice between monitoring and trading (Shleifer and Vishny, 1986). Long-term ownership is expected to create incentives to engage in corporate monitoring and thus to specialize more in monitoring than in trading. Chidambaran and John (1998) argue that a long-term investment horizon creates incentives to improve shareholder value by imposing disciplinary mechanisms on managers to align their interests with those of shareholders and leads to "relationship investing" refers to the active cooperation between an institutional shareholder and the manager of a firm. Chen, Harford, and Li (2007), Elyasiani and Jia (2008), Elyasiani and Jia (2010), Elyasiani, Jia, and Mao (2010) and Attig, et al. (2012), among others, find that concentrated holdings by independent institutional investors with a long-term horizon leads to increased monitoring and is related to better public firm performance.

Thus, investors' demand for firm monitoring is an increasing function of their investment horizon. But if long-term equity investors tend to be active shareholders, they are also passive investors whose asset-allocation decisions require that long-term expectations about risk and returns, that is, investment benchmarks, be met. In the case of frequently traded assets, market prices provide the basis for these expectations. In effect, private monitoring efforts by large block holders contribute to market efficiency, since they also benefit other stockholders. In turn, the market also provides monitoring benefits to long-term investors by processing information that is not available privately (see Holmström and Tirole (1993)).

Unlisted equity and the failure of delegated monitoring

Investing in infrequently traded assets also requires a longer investment horizon, hence it is a de facto asset-allocation decision for investors. However, without the feedback of market prices, the formation of long-term expectations about risk and returns is less straightforward. It follows that investing in unlisted equities must increase investors' monitoring demand. As is the case with listed firms, for unlisted firms, a long-term investment horizon creates incentives to monitor performance to preserve or improve shareholder value, but their illiquid nature also creates a second motive for monitoring: investment benchmarking.

The ability of unlisted firms to meet investors' demands for continuous performance monitoring determines their attractiveness. Achieving effective allocation requires understanding performance, but inadequate performance measurement also leads to a regulatory dead end: when faced with unknown quantities, prudential regulation penalizes long-term unlisted bets, further distorting allocation decisions.

Hence, for investors to make substantial investments in unlisted firms, such as unlisted infrastructure equity, they have to be in a position to make a strategic asset-allocation decision and this, in turn, requires substantial and continual performance monitoring of comparable assets. In Bayesian terms, long-term investing in listed equities is based on a prior benchmark, formed with historical market data (passive investment), but also leads to active shareholder management, potentially improving firm performance and also contributing to market efficiency (information revelation). At the next period, the updated (posterior) market benchmark can be used to revise the initial asset allocation. With unlisted equity, arriving at a prior asset allocation decision cannot be based on market prices unless near-equivalent traded assets can reliably be found. If they cannot, monitoring comparable unlisted instruments is necessary to form long-term expectations about performance and will serve as a basis for asset allocation. Once the investment has been made, both the motive to act as an active shareholder and that of being a passive investor (investing according to a benchmark) continue to support an investor's inter-temporal monitoring demand. Continued updating of investors' knowledge about performance requires ongoing monitoring because the information feedback loop created by market prices is now absent.

Next, investing in unlisted, illiquid firms with a long-term horizon requires specialist knowledge and should lead investors to delegate this process to investment managers. Unfortunately, the current delegated model of private equity investment mostly fails to respond to investors' intertemporal monitoring demand. This is most apparent with the kind of performance reporting offered by private equity (PE) managers.

Phalippou and Gottschalg (2009) propose a comprehensive critique of the performance monitoring of typical private equity funds. They highlight the well-known finding that to ensure consistent internal rates of return (IRRs), dividends and borrowing must respectively be reinvested and maintained at the same rates—an assumption that is nearly impossible to replicate in practice.

Pooling individual investment and fund IRRs also creates misleading results because IRRs cannot be averaged. The authors also find a large negative correlation between duration and performance in private equity funds, which, combined with the incentive to time cash flows strategically, tends to create an upward bias in reported performance and creates incentives to exit investments quickly.

In effect, IRRs are grossly inadequate for the purpose of asset allocation. As long as PE was a subplot of the alternative investment universe, the absence of a clear benchmark did not stop investors from committing funds to "absolute return" strategies. However, the growing interest in unlisted assets among large institutional investors with long investment horizons requires that the question of unlisted equity performance be answered seriously.

The end of delegation?

With unsatisfactory performance measurement and monitoring by PE managers, as well as potentially misaligned reporting incentives, a number of large institutional investors have ceased to delegate their investments in unlisted firms and have instead internalized the function of acquiring and managing infrequently traded assets, such as real estate, industrial firms (which are still often called - private equity) or infrastructure. This trend towards direct investment in illiquid assets is most developed among Canadian pension funds, a few large European pension funds and sovereign wealth funds.

Thus, because long-term investment in unlisted firms leads to a significant increase in the demand for performance monitoring, and because the PE industry has been mostly incapable or unwilling to provide better monitoring to investors, in particular the kind of performance measure that would be meaningful for asset allocation, the largest investors have resorted to internalizing the investment and monitoring functions necessary to access and benefit from unlisted equity.

This is not necessarily an improvement. Delegation to a specialist agent should improve efficiency. It is only because information asymmetries between investors and managers can be large enough to destroy all the benefits from delegation, that a number of large investors have decided to abandon delegated PE altogether. Nevertheless, internalizing creates other costs. In particular, as discussed by Blanc-Brude (2013), it can be difficult to create a well-diversified portfolio of large illiquid assets such as infrastructure project equity. Moreover, this approach is only available to very large investors, who can bear the full cost of deal sourcing and the ongoing management of their portfolio companies.

Faced with a retreat from such large accounts as the Canadian pension industry, why are PE managers not offering to improve their monitoring and reporting so that investors can benefit from delegation while making well-informed asset-allocation choices? One explanation is that in a world where some PE managers are capable of making the costly effort to deliver high-quality services and others are not, when information asymmetries between investors and managers are sufficiently large managers tend to pool together and offer only the low-effort service at the same high fees.[9]

Some managers are already evolving toward new PE models, allowing investors to gain the kind of longer-term exposure they require. Moreover, the tendency for institutional investors to create large or very large unlisted equity allocations is a recent development and the need to monitor and benchmark performance has only recently become more pressing.

But the failure of the PE industry to provide satisfactory monitoring for large investors is also a collective action problem: most of the necessary information is private; dissemination

[8] As opposed to a distressed sale.
[9] This is a standard result of agency theory known as a "pooling equilibrium" (see Laffont and Martimort 2002).

and data collection, when they exist, are more or less ad hoc. While PE managers could be more transparent and try to provide performance measures that are more relevant to long-term investors, taken individually, none of them has access to enough information to answer the question of PE asset allocation.

How to make unlisted infrastructure investment relevant to institutional investors

Effective and efficient long-term institutional investment in unlisted infrastructure must combine preserving the benefits of delegation to a specialist manager who can act on behalf of an active shareholder, while enforcing sufficient long-term performance monitoring and benchmarking to allow a passive investment stance, justified as the strategic asset-allocation level.

To achieve this, we propose steps to require a multi-stakeholder effort to reveal the characteristics of infrastructure assets at the underlying and portfolio levels, and reduce information asymmetries between investors and managers.

1. DEFINITION: The first step is an unambiguous definition of the underlying asset as a financial instrument. As we have argued before (Blanc-Brude, 2013) infrastructure assets are not real assets and from an investment perspective, industrial classifications are close to useless.

2. VALUATION AND RISK MEASUREMENT TECHNOLOGY: With a clear and well-accepted definition of underlying instruments, adequate valuation and risk measurement methodologies can be developed that take into account infrequent trading. By adequate we mean that such methodologies should rely on the rigorous use of asset-pricing theory and statistical techniques to derive the necessary input data, while aiming for parsimony and realism in terms of data collection. The proposed methodologies should lead to the definition of the mininum data requirement (MDR) necessary to derive robust return and risk estimates.

3. DATA COLLECTION REQUIREMENTS: While ensuring theoretical robustness is paramount to the reliability of performance measurement, it must be balanced with the requirement to collect real-world data from market participants. Proposed methodologies should particularly aim to minimize the number of inputs in order to limit parameter estimation errors. Adequate models should also focus on using data points that are known to exist and that have been, or that could easily be, collected and monitored. In all cases, data requirements should be derived from the theoretical framework, not the other way around. Whether the necessary data exist or not, this process will also inform the standardization of investment data collection and reporting.

4. REPORTING STANDARD: The standardization of infrastructure investment data collection should allow the emergence of an industry-wide reporting standard, which can be recognized by investors and regulators alike. Such a reporting standard would increase transparency between investors and managers, who would now be mandated to invest in a well-defined type of instrument and commit to reporting enough relevant data for investors to benefit from their specialized monitoring.

5. INVESTMENT BENCHMARKS: Once the investment profile of the underlying asset has been documented as well as existing data allow, spanning expected returns, risk and market correlations, investment benchmarks can be designed to reflect the performance of a given strategy (e.g., maximum Sharpe ratio) for a given horizon. If such benchmarks are found to improve the investible set then investment solutions can be designed.

6. INVESTMENT SOLUTIONS: These investment benchmarks can serve as the basis for the development of various standard or tailored investment solutions by the industry, including different types of funds with explicit horizons and risk profiles.

7. REGULATION: The robust performance benchmarking of unlisted infrastructure equity portfolios also has direct regulatory implications for risk-based prudential frameworks like Solvency II. It should allow the calibration of, for example, a dedicated unlisted infrastructure sub-module in the context of the standard formula, or usefully inform investors' internal risk models.

8. PUBLIC PROCUREMENT: Finally, documenting the financial performance of unlisted infrastructure is relevant for the design of public infrastructure tenders and contracts. It is the opportunity for the public sector to involve investors early in the design of public infrastructure contracts on the basis of an academically-validated and industry-recognized measure of investment performance.

Recent progress

In recent publications, we have begun to highlight some of our proposed answers to this roadmap, in particular, the definition of underlying assets and the methodologies required to measure value and risk adequately, with parsimonious data inputs.

Definition: project finance as the infrastructure investment benchmark

It is often said that there is no universally accepted definition of infrastructure. For a long time, the energy sector (coal and gas-fired power plants, wind power, etc.) was considered to be separate from infrastructure, understood as network utilities (water, road and gas networks). Today, with the growing popularity of infrastructure as an investment topic, more industrial sectors are covered by the umbrella term of infrastructure. In our view, the definition of what constitutes physical infrastructure is unimportant. The terminology is close to meaningless from an investment point of view, since it does not refer to a specific type of financial instrument or investible asset.

Defining infrastructure investment for strategic asset allocation helps determine expected returns, risk and market correlations, in short: the existence of a distinctive or remarkable beta. If infrastructure investment is defined in such a way that it overlaps significantly with existing betas (e.g., venture capital or corporate debt) then this definition does not help in allocating funds to infrastructure assets.

In the case of long-term and infrequently traded assets like infrastructure, an approach that relies on large amounts of historical data cannot dependably isolate the relevant characteristics. There will never be enough data. Hence, we need to think about the determinants of risk, return and correlations of such assets through ex-ante models, which can then be tested and calibrated, but which necessarily assume the existence of certain mechanisms explaining risk and value in time. Consequently, our definition of underlying infrastructure assets must treat these mechanisms explicitly.

A definition of infrastructure investment based on explicit economic and financial mechanisms that are expected to determine the value and the volatility of cash flows will also present the advantage of being clear and uncontroversial. Nevertheless, there is a trade-off between clarity and scope. The explicit formulation of underlying mechanisms must almost certainly restrict our definition to a subset of what is commonly understood to be infrastructure. Again, from a pure investment point of view, this is not a problem.

Our proposed solution in a forthcoming paper (Blanc-Brude and Ismail, 2014) is to define the underlying asset in infrastructure investment using the Basel II definition of Project Finance (BIS, 2005), i.e., a special-purpose entity (SPE) dedicated to the construction and operation of a new infrastructure project over a given period, typically 25 to 30 years. In effect, most infrastructure investment and the immense majority of new projects are financed using such structures.[10]

Crucially, existing research on project financing concludes that it is an unusual form of corporate governance relying extensively on contractual arrangements to manage risks and in which both equity investors and lenders play an important structuring and monitoring role (see Blanc-Brude and Ismail, 2013, for a review of the literature). Hence, project finance provides a well-defined model of generic underlying investments, which may be calibrated, and the exposure to which may or may not be relevant for investors.

Adequate methodologies to measure value and risk in infrastructure project finance equity are proposed in a forthcoming paper (Blanc-Brude and Ismail, 2014) and briefly discussed below.

Methodology: measuring value and risk in incomplete markets

Standard asset pricing theory relies on a demanding framework of market completeness and efficiency, which is at odds with the valuation of infrequently traded assets like infrastructure equity. Even without relaxing the assumption of market efficiency, by which enough information is available to rational investors to arrive at arbitrage free prices, the assumption that markets are complete is difficult to maintain; it is not clear that there exists a set of contingent claims that could be used to continuously hedge the value of infrastructure equity stakes.

Indeed, while the equity investor in an infrastructure project can always be described as writing a call option on the project's free cash flow (with the debt service as the strike price), there is no traded instrument representing the free cash-flow process that could be combined with a risk-free bond to replicate the pay-off of the call option. If investors cannot continuously hedge the call option, their valuations will not converge toward a specific pricing measure.

[10] *We estimate that more than USD 3 trillion of project financing was closed worldwide between 1995 and 2012 (Blanc-Brude and Ismail, 2013).*

...the growing interest in unlisted assets among large institutional investors with long investment horizons requires that the question of unlisted equity performance be answered seriously.

So, in an incomplete market setup, individual investors will arrive at different valuations. In other words, there is no single set of discount rates of the expected payoff. Instead, individual investor risk preferences determine their cost of capital for a given expected payoff. In other words, it is inadequate to use standard option pricing (assuming risk neutral pricing) to value infrequently traded assets that cannot be easily replicated with traded assets. Likewise, CAPM approaches imply the law of one price. Instead, adequate and rigorous infrastructure equity valuation must be developed using an incomplete market setup. Valuing infrequently traded assets also affects the adequate choice of statistical inference techniques. Both investors and researchers start the process of valuing infrastructure assets from a position of relative ignorance and gradually learn about the value of the model's parameters. It is a Bayesian process of learning, during which our prior knowledge of the value of model parameters is updated by observing the behavior of infrastructure equity investments.

Starting from the necessarily subjective dimension of infrastructure equity pricing, we propose a first approach to valuation and risk measurement in Blanc-Brude and Ismail (forthcoming 2014). Building on El Karoui and Quenez (1995), we suggest that while individual investors value infrastructure equity investment subjectively, there exist objective bounds to their valuation. These upper and lower limits, or arbitrage bounds, encompass the valuations that different investors would reasonably arrive at. The methodological challenge is to formulate and then shrink these bounds in order to arrive at a sufficiently narrow band of valuations and potential returns.

Risk measurement is also addressed from a subjective perspective: each instance of project finance leads to the explicit definition of an investment base case, a notional series of cash flows representing the initial equity investment proposition. This base case is risky and does not represent the expected cash flows in the statistical sense. In effect, any observed divergence from base case cash flows can be regarded as the risk faced by investors following their subjective appreciation of the investment proposal at t_0. In Blanc-Brude and Ismail (forthcoming 2014), we show that if we can observe and explain the tendency of infrastructure-project finance equity cash flows to diverge from their base case, we can derive relevant risk measures without having to value assets explicitly.

Next step: data collection

Relevant methodologies to value infrastructure equity stakes will continue to be developed, but their significance will depend on their data collection requirements. In Blanc-Brude and Ismail (forthcoming 2014) we also define the minimum amount of data that needs to be collected to implement our proposed methodologies. Widespread data collection using a standardized format, leading up to an industry recognized reporting standard for infrastructure investment managers, is the next important step on the road to building investment solutions in infrastructure that are relevant to institutional investors.

A major effort remains to be made by investors, managers, regulators and academics to contribute to the development of relevant investment solutions in infrastructure assets, including state-of-the-art methodologies and the definition of the minimum data required to implement them and answer benchmarking and asset allocation questions seriously. Market players must also embrace the standardized and transparent reporting of underlying cash-flow data for these benchmarks to become a reality.

EDHEC-Risk Institute will continue to support and contribute to this effort in the years to come.~

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

The purpose of this chair is to provide a better understanding of the nature and investment profile of equity investment in infrastructure assets. It will focus on fostering data collection and aggregation from investors and on improving the benchmarking of return distributions for direct and indirect investment in infrastructure equity by developing an academically-validated and industry-recognized index.

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INDEXES

Smart Beta 2.0: A Powerful Concept for Multi Smart Factor Investing

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

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

Ashish Lodh
Senior Quantitative Analyst
ERI Scientific Beta

Recently there has been a significant increase in the number of alternative forms of equity indexes. Given so much choice, investors must decide which index to select. The selection depends on the investment objective and, more important, on the risk preference of the investor. Therefore, a more relevant question is how best to reward investors for the risk choices they wish to make? A good smart-beta index is one that diversifies away the specific risks and manages the exposure to equity risk factors. This article shows how to construct smart (well diversified) factor indexes and the benefits gained from diversifying across them the multi smart factor approach.

From multi-strategy investing…

It is useful to recall that each diversification-based weighting scheme comes with systematic (or rewarded) risks, specific risks, and more generally, non-rewarded risks.

Systematic risks are well known to researchers and investment practitioners. Today, they are the subject of numerous commercial propositions, notably from index providers who, arguing that traditional cap-weighted indexes have exposures to the wrong factors, offer solutions with more favorable factor biases, such as value or size for example.

By mixing weighting schemes with factor exposures that can differ (for example, an equal-weighted or maximum-deconcentration weighting scheme will have a more pronounced exposure to the size factor than a minimum-volatility scheme, which will be more exposed to low volatility stocks), the multi-strategy approaches diversify the systematic risk factors and smooth the performance and the risks relative to cap-weighted schemes.

However, this factor does not take account of the seminal work of Harry Markowitz, which addresses the diversification of specific risks. The category of specific risks corresponds to all the risks that are non-rewarded in the long run, and therefore not ultimately desired by the investor, but that can have a strong influence on the volatility or the maximum drawdown of the index (in absolute terms) or the tracking error or maximum relative drawdown of the index (in relative terms). Specific risks can correspond to important financial risk factors that do not explain, over the long term, the value of the risk premium associated with the index. There are many of these non-rewarded financial risk factors. The academic literature considers for example that commodity, currency or sector risks do not have a positive long-term premium. These risks can have a strong influence on the volatility, tracking error, maximum drawdown or maximum relative drawdown over a particular period, which might sometimes be greater than that of systematically rewarded risk factors (e.g., exposure to the financial sector during the 2008 crisis or to sovereign risk in 2011). In line with portfolio theory, among the non-rewarded financial risks we also find specific financial risks (also called idiosyncratic stock risks) that correspond to the risks that are specific to the company itself (its management, the poor quality of its products, the failure of its sales team, the relevance of its R&D and innovation, etc.). It is this type of risk that asset managers are supposed to be the best at recognizing, evaluating and choosing in order to create alpha, but portfolio

EXHIBIT 1

Diversified Multi-strategy

The table shows conditional relative returns and conditional tracking error of five diversification-based indexes and the Diversified Multi-strategy index, an equal-weighted combination of the five indexes. All statistics are annualized, all portfolios are rebalanced quarterly and the analysis is based on daily total returns (with dividends reinvested) from 06/21/2002 to 12/31/2012 for short term and from 12/31/1972 to 12/31/2012 for long term. The total number of stocks in the USA universe is 500 and in Developed ex USA universe is 1,500. Calendar quarters with positive market index returns comprise bull markets and the rest constitute bear markets. Source: www.scientificbeta.com and CRSP.

Scientific Beta USA Indexes						
USA Short Term	Maximum Deconc.	Maximum Decorr.	Efficient Min Volatility	Efficient Max Sharpe	Diversified Risk Parity	Diversified Multi-Strategy
Ann. Relative Returns						
Full Period	1.80%	1.69%	2.59%	1.88%	2.00%	2.01%
Bull Market	4.23%	2.33%	-1.37%	1.28%	2.40%	1.77%
Bear Market	-0.62%	1.14%	6.89%	2.55%	1.55%	2.28%
Ann. Tracking Error						
Full Period	3.28%	3.33%	4.42%	3.18%	2.79%	2.84%
Bull Market	2.86%	2.90%	3.50%	2.62%	2.42%	2.41%
Bear Market	3.90%	3.97%	5.68%	3.98%	3.32%	3.45%

Scientific Beta USA Indexes						
USA Long Term	Maximum Deconc.	Maximum Decorr.	Efficient Min Volatility	Efficient Max Sharpe	Diversified Risk Parity	Diversified Multi-Strategy
Ann. Relative Returns						
Full Period	2.39%	2.42%	2.46%	2.69%	2.45%	2.50%
Bull Market	4.34%	3.33%	-0.07%	2.33%	3.17%	2.63%
Bear Market	-0.08%	1.16%	5.38%	2.91%	1.41%	2.15%
Ann. Tracking Error						
Full Period	2.39%	2.42%	2.46%	2.69%	2.45%	2.50%
Bull Market	3.85%	3.87%	4.51%	3.86%	3.69%	3.72%
Bear Market	5.15%	5.23%	6.61%	5.69%	5.17%	5.25%

Scientific Beta Developed ex USA Indexes						
Developed ex USA Short Term	Maximum Deconc.	Maximum Decorr.	Efficient Min Volatility	Efficient Max Sharpe	Diversified Risk Parity	Diversified Multi-Strategy
Ann. Relative Returns						
Full Period	2.00%	2.30%	3.22%	2.64%	2.30%	2.51%
Bull Market	3.46%	1.26%	-1.74%	0.57%	2.11%	1.14%
Bear Market	0.39%	3.39%	8.77%	4.84%	2.41%	3.93%
Ann. Tracking Error						
Full Period	2.79%	3.57%	5.34%	3.89%	2.96%	3.46%
Bull Market	2.16%	2.73%	4.21%	3.00%	2.29%	2.66%
Bear Market	3.80%	4.93%	7.18%	5.32%	4.04%	4.74%

theory considers it to be neither predictable nor rewarded, so it is better to avoid it by investing in a well-diversified portfolio. A globally effective diversification weighing scheme reduces the quantity of non-rewarded risk, whether it involves non-rewarded risk factors or non-rewarded specific financial risks. However, like any model, it is imperfect and can itself lead to significant residual exposures to certain non-rewarded risks. For example, minimum-volatility portfolios, which are robust proxies for efficient portfolios and therefore well diversified, are often exposed to significant sector biases. Diversification models that are exposed as little as possible to these non-rewarded risks should be used. For example, norm constraints can balance the desire to efficiently reduce the volatility of a minimum-volatility weighting scheme, while avoiding overconcentration in a small number of low-volatility stocks. Specific or non-rewarded risks can also correspond to operational or non-financial risks that are specific to the diversification model. We call these risks "strategy" or "operational-specific" risks, which we usually analyze using the concept of parameter estimation error. For example, a maximum decorrelation scheme depends on an accurate estimation of the correlation matrix for the robustness of the diversification proposed. Every investor should attach a high price to the technical quality of the models used and their implementation to reduce this type of specific risk (for example, the quality of the estimation of correlation matrices is a crucial element for the majority of diversification weighting schemes and has been the subject of much econometric, economic and statistical effort in recent years).

In spite of all the attention paid to the quality of model selection and the implementation of these models, this specific operational risk, like the non-rewarded financial risks described above, remains present, and it therefore seems important to reduce even further the exposures that each weighting scheme, even if it is smart, is not able to diversify. This is also the objective of our multi-strategy approach, which ultimately enables not only the systematic risks, but also the specific or non-rewarded risks, to be diversified.
This double effect is illustrated in Exhibit 1

…to multi smart factor investing

Any deviation from the standard cap-weighting approach will potentially lead to exposures to equity risk factors (betas) that are different from the cap-weighted references. Investors should select the risk factors to which they want to be exposed. With betas being the key ingredients of active management, asset managers have become aware of the importance of managing betas and their diversity. Indexes or building blocks replicating microeconomic factors (like size, momentum, value, liquidity or volatility) and macroeconomic factors (like geographical region or industry sector) can be found in abundance on the market.

Beyond pure factor replication is the issue of harvesting the risk premium of these betas. Plenty of empirical evidence shows that cap-weighted indexes are not well diversified, efficient benchmarks; they do not provide fair compensation for the amount of risk taken (Haugen and Baker, 1991, Grinold, 1992). We propose a solution for this in the form of smart-factor investing. The idea of smart-factor investing is to construct a factor-tilted portfolio to extract the factor premia most efficiently and is based on 1) selecting appropriate stocks for the desired beta and 2) using a diversification-based weighting scheme.

A clear distinction between the stock selection phase and the weighting phase enables investors to choose the risks to which they wish to be exposed. This choice of risk can be expressed through an explicit choice of the universe in which the strategy invests.[11] When stock selection is based on a particular stock-based characteristic, such as size, it allows this factor exposure to be shifted, regardless of the weights that are applied to individual portfolio components.

Once the risk is chosen, one or more smart weighting schemes can be used to provide a well diversified portfolio corresponding to a smart proxy for the factor exposure. We call this proxy smart because, unlike investible factor proxies constructed with maximum factor loading or cap-weighted-schemes, the Scientific Beta factor-tilted indexes are diversified,

EXHIBIT 2

Multi-smart factor Diversification
The table presents absolute and relative risk/return analysis of factor-tilted diversified multi-strategy indexes. 95% tracking error is the 95th percentile of the tracking error computed using a rolling window of one year and step size of one week. The yield on Secondary Market U.S. Treasury Bills (3M) is a proxy for the risk-free rate. All statistics are annualized, all portfolios are rebalanced quarterly and the analysis is based on daily total returns (with dividends reinvested) from 06/21/2002 to 12/31/2012 for short term and from 12/31/1972 to 12/31/2012 for long term. The total number of stocks in the USA universe is 500 and in the Developed ex USA universe is 1,500. Factor-tilted indexes contain 50% stocks sorted by the characteristics (size, volatility, B/M ratio, and liquidity). Source: www.scientificbeta.com and CRSP

Scientific Beta USA Diversified Multi-strategy

USA Short Term	USA CW	Mid Cap	Low Volatility	Value	Mid Liquidity	Avg of 4 Smart Factor Indexes	Multi-Beta -Multi-Strategy
Ann. Returns	5.99%	9.10%	8.04%	8.92%	8.60%	8.67%	8.70%
Relative Returns	-	3.12%	2.05%	2.94%	2.61%	2.68%	2.72%
Ann. Volatility	21.21%	21.05%	17.67%	21.28%	19.29%	19.82%	19.68%
Sharpe Ratio	0.20	0.35	0.36	0.34	0.36	0.35	0.36
Tracking Error	-	4.54%	5.48%	3.87%	4.66%	4.64%	3.83%
95% Tracking Error	-	7.15%	9.62%	5.32%	7.21%	7.32%	6.03%
Information Ratio	-	0.69	0.37	0.76	0.56	0.59	0.71

Scientific Beta Long Term USA Diversified - Multi-strategy

USA Long Term	Long Term USA CW	Mid Cap	Low Volatility	Value	Mid Liquidity	Avg of 4 Smart Factor Indexes	Multi-Beta -Multi-Strategy
Ann. Returns	9.74%	14.19%	12.64%	14.59%	13.99%	13.85%	13.91%
Relative Returns	-	4.45%	2.90%	4.85%	4.25%	4.11%	4.17%
Ann. Volatility	17.47%	16.73%	14.39%	16.54%	15.60%	15.81%	15.64%
Sharpe Ratio	0.24	0.52	0.50	0.55	0.54	0.53	0.54
Tracking Error	-	6.80%	6.17%	5.81%	7.03%	6.45%	5.99%
95% Tracking Error	-	11.55%	11.51%	10.17%	12.50%	11.43%	10.66%
Information Ratio	-	0.66	0.47	0.83	0.61	0.64	0.70

Scientific Beta Developed ex USA Diversified - Multi-strategy

Developed ex USA Short Term	Developed ex USA CW	Mid Cap	Low Volatility	Value	Mid Liquidity	Avg of 4 Smart Factor Indexes	Multi-Beta -Multi-Strategy
Ann. Returns	7.71%	10.67%	11.40%	10.73%	10.82%	10.91%	10.94%
Relative Returns	-	2.96%	3.69%	3.02%	3.11%	3.20%	3.23%
Ann. Volatility	19.32%	16.43%	15.11%	18.58%	16.47%	16.65%	16.54%
Sharpe Ratio	0.31	0.55	0.64	0.49	0.56	0.56	0.56
Tracking Error	-	5.27%	5.92%	3.63%	5.61%	5.10%	4.68%
95% Tracking Error	-	9.09%	9.77%	5.55%	9.93%	8.59%	7.98%
Information Ratio	-	0.56	0.62	0.83	0.55	0.64	0.69

[11] *A distinction between stock universe selection and the selection of a diversification-based weighting scheme recognizes that, in principle, methodological choices can be made independently in these two steps, which are used in the construction of advanced beta equity strategies. This is the flexibility offered in the Smart Beta 2.0 approach.*

and so reduce the exposure to non-rewarded risks, providing more efficient access to the return associated with the factor.

We then construct smart-factor indexes: building blocks that use diversified multi-strategy weighting on characteristics-based half universes.[12] Stock choices are made to gain exposure to three well-known equity risk factors: size, value- and liquidity, along with the low volatility factor, which is commonly accepted to have a positive risk premium (an anomaly). Then we construct a multi-beta, multi-strategy index that combines the four factor-tilted indexes in equal proportion, with an objective of achieving lower tracking error. Exhibit 2 shows that the multi-beta, multi-strategy index results in tracking error that is below the average tracking error of the constituting indexes. Since its performance is close to the average performance of the constituents, its information ratio shows a significant improvement. Results show that diversification across factors also helps in controlling extreme relative risks. In the three cases presented in Exhibit 2, the 95% tracking error of the multi-beta strategy is either less than or very close to the lowest 95% tracking error achieved by the constituents

Exhibit 3 summarizes the benefits of diversification across strategies and diversification across betas. In the U.S. long-term analysis, the Sharpe ratio increases from 0.38 to 0.41 by going from naïve diversification (maximum deconcentration) to multi-strategy, while taking no explicit factor bets. The Sharperatio is 0.48 when the combination of betas is used within the maximum deconcentration weighting—a multi-beta index. It further increases to 0.54 when the smart-factor indexes are combined to form a multi-beta, multi-strategy index. ~

CONCLUSION

The objective of Smart Beta 2.0 is the management of both specific risk, or non-rewarded risk, and systematic risks, or rewarded risks. The strategy-specific risk can be optimally diversified by combining different weighting schemes. Investors, and not smart-beta providers, should have the freedom to select the systematic risks to which they want to be exposed and to manage them. Multi-beta indexes, which allow for a flexible choice and combination of smart-factor indexes, present new opportunities for passive investors or for active managers and multi-managers to enhance their performance at very low marginal cost.

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EXHIBIT 3

Sharpe Ratio Improvement

The table shows the improvement gained in Sharpe ratio by diversifying across strategies and by diversifying across 4 betas: - mid cap, low volatility, value, and mid liquidity. All statistics are annualized, all portfolios are rebalanced quarterly and the analysis is based on daily total returns (with dividends reinvested) from 06/21/2002 to 12/31/2012 for short term and from 12/31/1972 to 12/31/2012 for long term. Source: www.scientificbeta.com and CRSP.

USA Short Term	Single Strategy (Max Deconcentration)	Diversified Multi-strategy
No explicit factor tilt (no stock selection)	0.27	0.31
Multi Beta (combination of 4 factor tilts)	0.32	0.36
USA Long Term	**Single Strategy (Max Deconcentration)**	**Diversified Multi-strategy**
No explicit factor tilt (no stock selection)	0.38	0.41
Multi Beta (combination of 4 factor tilts)	0.48	0.54
Developed ex USA Short Term	**Single Strategy (Max Deconcentration)**	**Diversified Multi-strategy**
No explicit factor tilt (no stock selection)	0.42	0.49
Multi Beta (combination of 4 factor tilts)	0.50	0.56

In spite of all the attention paid to the quality of model selection and the implementation of these models, this specific operational risk, like the non-rewarded financial risks described above, remains present, and it therefore seems important to reduce even further the exposures that each weighting scheme, even if it is smart, is not able to diversify.

[12] *Diversified multi-strategy has been chosen as the weighting scheme following the diversification across weighting schemes argument present in the first part of this article. In theory, one can choose any diversification-based (non-cap-weighted) weighting scheme to construct smart-factor indexes.*

INDEXES

How Robust is the Outperformance of Smart Beta Equity Strategies?

Ashish Lodh
Senior Quantitative Analyst
ERI Scientific Beta

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

Accounting for the risks of smart beta

There has been increasing interest in so-called smart-beta strategies[rom] that try to generate outperformance over standard market indexes. These indexes are being marketed on the basis of a number of shortcomings of cap-weighted indexes that have been documented to be overly concentrated (see Tabner, 2007, and Malevergne, et al., 2009) and to provide poor risk-adjusted returns (see Goltz and Le Sourd, 2010, for a literature review). As an alternative to cap-weighted indexes, numerous advanced beta equity offerings have been launched that draw either on firm fundamentals or on risk/return parameters to construct systematic equity portfolios.

Providers of such indexes have widely documented the superior performance of their respective approaches compared to the corresponding cap-weighted indexes. In early papers, such performance comparisons have fallen short of fully accounting for risks of such strategies (see Arnott, Hsu, and Moore, 2005, as an example of a paper that does not even report the exposure of the strategy to standard risk factors such as small cap and value factors.[13]

While it is now commonly accepted that moving away from cap-weighting tends to enhance diversification and improve risk-adjusted performance over long horizons, it has to be recognized that each alternative weighting scheme will expose an investor to a risk of underperforming cap-weighted reference indexes over short investment horizons. Moreover, it seems reasonable to assume that certain market conditions may influence the capacity of a given weighting scheme to provide outperformance over cap-weighted reference indexes. It is thus crucial for investors to assess the risk of underperformance as well as the conditional performance profile of any smart-beta strategy so as to gain a better picture of the robustness of the potential outperformance of a strategy.

The remainder of this article provides an analysis of relative risk and of conditional performance properties of a set of smart-beta strategies.

Global relative risk

Alternative index construction schemes lead in principle to an exposure to risk that deviates substantially from that of cap-weighted reference indexes, since they involve choices of factor exposure that are different from those of cap-weighted indexes. Investment professionals who deviate from cap-weighted indexes take on considerable reputation risk, as cap-weighted indexes represent a common reference for their peer group. It is thus crucial to analyze this relative risk properly. A common relative risk measure is the tracking error. However, in addition to such an average measure of relative risk, investors also pay attention to extreme realizations of relative risk, relative drawdowns and probability of outperformance. The Exhibit 1 provides a set of global relative risk measures that indicate the risk of deviating from the performance of a cap-weighted reference index for a range of smart-beta indexes for U.S. equities.

EXHIBIT 1

Relative Performance and Risk Analysis of Smart-beta U.S. Equity Strategies

Probability of outperformance is the historical empirical probability of outperforming the benchmark over a typical investment horizon of 1, 3 or 5 years irrespective of the entry point in time. It is computed using a rolling window analysis with 1, 3, or 5 years' window length and one week step size. Maximum relative drawdown is the maximum drawdown of the long-short index whose return is given by the fractional change in the ratio of strategy index to the benchmark index. Based on daily total returns from 01/01/1973 to 12/31/2012. The stock universe is the S&P 500 universe from CRSP.

	Max Deconcentration	Max Decorrelation	Efficient Min Vol	Efficient Max Sharpe	Diversified Risk Parity	Diversified Multi Strategy
Ann. Relative Returns	2.39%	2.42%	2.46%	2.69%	2.45%	2.50%
Tracking Error	4.32%	4.36%	5.29%	4.54%	4.23%	4.28%
Information Ratio	0.55	0.55	0.46	0.59	0.58	0.58
Outperf Prob (1Y)	65.3%	71.5%	72.6%	71.3%	69.1%	72.2%
Outperf Prob (3Y)	72.3%	79.0%	79.6%	79.9%	76.3%	78.6%
Outperf Prob (5Y)	78.3%	82.1%	79.9%	83.5%	80.6%	81.4%
Max Relative Drawdown	30.07%	30.00%	40.10%	30.66%	34.10%	32.89%

13 *While the paper shows results for a single factor regression, in particular the alpha of the alternative index with respect to a single market factor, and provides a detailed discussion of these results, the paper only loosely refers to the existence of small cap and value exposure without, however, showing any results to the reader.*

...it is important for investors to be aware of the short-term risks and to be able to sustain their investment in smart-beta strategies during periods of drawdowns

It is clear that, while all smart-beta strategies show pronounced outperformance in excess of 2% annualized, they all face significant drawdowns during the forty-year period under analysis, with the worst drawdowns exceeding 30% for all strategies. The probability of outperformance over any 1-year holding period is less than 70% for some strategies. However, when increasing the holding period to 5 years, outperformance probabilities exceed 80% for many strategies, showing that it is important for investors to be aware of the short-term risks and to be able to sustain their investment in smart-beta strategies during periods of drawdowns.

Conditional performance

Comparing performances under different market conditions helps explain an index's performance. Moreover, an analysis of the dependence of a strategy's short-term performance on market conditions allows the robustness of a strategy's performance to be assessed. The table below conducts a performance analysis separately for periods during which stock prices are rising and investor sentiment is strong (bull markets) and periods with declining market prices and weak investor sentiment (bear markets).

The conditional performance properties of different smart-beta strategies show pronounced differences. For example, while the Maximum Deconcentration strategy and the Efficient Minimum Volatility strategy show comparable levels of annualized relative returns over the cap-weighted index and outperformance probability over five years, they show very different dependence on market conditions. The Maximum Deconcentration strategy generates outperformance during bull markets and slight underperformance in bear markets while the Efficient Minimum Volatility strategy shows pronounced outperformance in bear markets and slight underperformance in bull markets.

Moreover, the Diversified Multi-strategy index, which combines five different weighting schemes, shows much less dependence on market conditions than its component strategies, as the different conditional performance profiles counterbalance each other when diversifying across strategies. For investors choosing a smart-beta strategy it is important to be informed of such dependencies so that they can make an appropriate choice of smart-beta strategy or combination of strategies. ~

EXHIBIT 2

Conditional Performance of Smart-beta U.S. Equity Strategies

Calendar quarters with positive market index returns comprise bull markets and the rest constitute bear markets. High-volatility market comprises the top 50% of quarters sorted on the quarterly cap-weighted benchmark's volatility and the low-volatility market comprises the rest. All statistics are annualized. The analysis is based on daily total returns from 01/01/1973 to 12/31/2012. The stock universe is the S&P 500 universe from CRSP.

Bull Markets	Cap Weighted	Max Deconcentration	Max Decorrelation	Efficient Min Vol	Efficient Max Sharpe	Diversified Risk Parity	Diversified Multi-strategy
Ann. Returns	31.8%	36.1%	35.1%	31.7%	34.1%	35.0%	34.4%
Ann. Volatility	14.4%	14.3%	13.7%	12.1%	13.2%	13.8%	13.4%
Sharpe Ratio	1.83	2.14	2.17	2.18	2.18	2.14	2.17
Ann. Relative Returns	-	4.3%	3.3%	-0.1%	2.3%	3.2%	2.6%
Tracking Error	-	3.8%	3.9%	4.5%	3.9%	3.7%	3.7%
Information Ratio	-	1.13	0.86	-0.02	0.60	0.86	0.71

Bear Markets	Cap Weighted	Max Deconcentration	Max Decorrelation	Efficient Min Vol	Efficient Max Sharpe	Diversified Risk Parity	Diversified Multi-strategy
Ann. Returns	-25.0%	-25.1%	-23.8%	-19.6%	-22.1%	-23.6%	-22.8%
Ann. Volatility	22.3%	22.5%	21.4%	19.0%	20.5%	21.5%	20.9%
Sharpe Ratio	-1.37	-1.37	-1.38	-1.33	-1.35	-1.36	-1.36
Ann. Relative Returns	-	-0.1%	1.2%	5.4%	2.9%	1.4%	2.1%
Tracking Error	-	5.1%	5.2%	6.6%	5.7%	5.2%	5.3%
Information Ratio	-	-0.01	0.22	0.81	0.51	0.27	0.41

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INDEXES

Long-Term Performance of Scientific Beta Indexes

Ashish Lodh
Senior Quantitative Analyst
ERI Scientific Beta

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

Modern portfolio theory (MPT) states that investors should allocate their wealth between a tangency portfolio, or a maximum Sharpe ratio (MSR) portfolio, and a riskless asset. Therefore, the only portfolio of risky assets that should be of interest to a rational investor is the MSR portfolio. Implementing Sharpe ratio maximization, however, is a complex task because of the difficulty of estimating risk for the required expected return and risk parameters. Therefore some diversification strategy indexes do not explicitly aim to achieve an optimal risk/reward ratio, but instead adopt heuristic approaches to diversification by trying to have fewer parameters to estimate or parameters whose estimation would be easier.

Heuristic, or ad-hoc, strategies, which have objectives different from Sharpe ratio maximization, can be further categorized into deconcentration and decorrelation based approaches. Deconcentration based strategies simply focus on reducing the weight and risk concentration of portfolios by spreading out the constituents' weights or their risk contributions equally.[14] Decorrelation strategies focus on reducing risk that stems from imperfectly correlated assets. In contrast to these heuristic approaches, scientific, or efficient diversification, methodologies are based on the theoretical framework of MPT and try to obtain efficient frontier portfolios, portfolios that obtain the lowest level of volatility for a given level of expected return (and thus the highest risk-adjusted return). All smart-beta strategies can be seen as a response to shortcomings of cap-weighted equity indexes like high concentration or risk-return inefficiency (Malevergne, Santa-Clara and Sornette, 2009, and Goltz and Le Sourd, 2011). ERI Scientific Beta proposes three heuristic diversification weighting schemes (maximum deconcentration, diversified risk parity and maximum decorrelation) and then two efficient diversification strategies, namely efficient minimum volatility and efficient maximum Sharpe (detailed description of methodologies can be found in Gonzalez and Thabault, 2013).

Most smart-beta indexes are marketed on the basis of outperformance, but usually their back-tests are conducted over a limited time period. Critics of smart beta often question the robustness of these strategies over the long term. Exhibit 1 shows that in the long term (40 years),[15] all the diversification strategies deliver higher returns than the cap-weighted reference index with annualized outperformance of more than 2.3%. Moreover, all of the diversification strategy indexes exhibit better risk-adjusted performance, with Sharpe ratios ranging from 0.38 to 0.45 (compared to 0.24 for the cap-weighted reference index). The efficient minimum volatility index delivers a volatility of 14.73% compared to 17.47% for the cap-weighted benchmark. The efficient maximum Sharpe ratio index results in a Sharpe ratio of 0.43, which is well above that of the cap-weighted index (0.24). Similarly, maximum deconcentration fulfills its deconcentration objective with an effective number of stocks equal to 485.[16] The maximum decorrelation objective can be accessed by computing the GLR measure, which can be viewed as the contribution of average pair-wise correlations to the volatility of the portfolio compared to that of a portfolio composed of

EXHIBIT 1

Overview of Diversification Strategies
The analysis is based on daily total returns from 12/31/1972 to 12/31/2012 (40 years). The regression coefficients statistically significant at the 95% level are in boldface. The market factor is the daily return of the cap-weighted index of all stocks that constitute the index portfolio in excess of the risk-free rate. The small size factor is obtained from Kenneth French's data library. The value (momentum) factor is the daily return series of a cap-weighted portfolio that is long the 30% highest and short the 30% lowest B/M ratio (past 1 year return) stocks in the CRSP S&P 500 universe. Secondary Market U.S. Treasury Bills (3M) is the risk-free rate in U.S. Dollars. Turnover is mean annual 1-way. All statistics are annualized.

	Cap Weighted	Max Deconcentration	Max Decorrelation	Efficient Min Vol	Efficient Max Sharpe	Diversified Risk Parity	Diversifie -Multi-strategy
Ann. Returns	9.74%	12.13%	12.16%	12.20%	12.43%	12.19%	12.24%
Ann. Volatility	17.47%	17.49%	16.67%	**14.73%**	15.99%	16.78%	16.28%
Sharpe Ratio	0.24	0.38	0.40	0.45	**0.43**	0.40	0.41
ENS	113	**485**	305	247	296	457	399
GLR	26.51%	19.75%	**18.29%**	18.99%	18.42%	20.23%	18.95%
Maximum DD	54.53%	58.70%	54.16%	50.03%	53.22%	56.36%	54.55%
Ann. Alpha	0.00%	**1.24%**	**1.23%**	**1.87%**	**1.58%**	**1.49%**	**1.49%**
Market Beta	**1.00**	**0.99**	**0.95**	**0.82**	**0.91**	**0.95**	**0.93**
Small Size Beta	-	**0.21**	**0.20**	**0.11**	**0.16**	**0.17**	**0.17**
Value Beta	-	**0.11**	**0.09**	**0.10**	**0.11**	**0.11**	**0.11**
MOM Beta	-	**-0.05**	0.01	**0.01**	**0.01**	**-0.04**	**-0.01**
Capacity (m$)	44 967	10 730	10 745	12 741	11 492	11 515	11 445
1-Way Turnover	2.66%	19.19%	27.65%	28.59%	26.31%	20.90%	19.12%

[14] *The risk contribution of a constituent is defined as the product of the constituent's weight with the marginal contribution of this constituent to the total portfolio volatility.*
[15] *All portfolios are constructed on the CRSP S&P 500 universe and are rebalanced quarterly.*
[16] *Effective number of stocks (ENS) is the inverse of the Herfindahl index,* $ENS = 1/\sum_{i=1}^{N} w_i^2$

uncorrelated stocks.[17] High turnover and limited investment capacity are two of the most cited problems with smart-beta indexes. Our results show that 1 way annual turnover of all diversification strategies is below 30%, showing the effectiveness of turnover rules. All strategies are adequately liquid; their weighted average market capitalization is about one quarter of that of the cap-weighted index, which is itself highly liquid by construction.[18]

Every smart-beta strategy carries risks, which can be divided into two categories: systematic risks and specific (or non-rewarded) risks. Systematic risks come from the fact that strategy indexes can be more or less exposed to dynamically rewarding systematic risk factors (such as value and size risk). Specific risks are the risks that are not desired by investors as they are not rewarded and can be reduced by diversification. They are composed of i) strategy-specific risk, which comes from the portfolio construction methodology, and ii) sample-specific risk, which comes from factors that influence return volatility over the course of the sample period, but are not necessarily rewarded in other words, they are not associated with a long-term risk premium.

The combination of different strategies allows the risks that are specific to each strategy to be diversified away by exploiting the imperfect correlation between the different strategies' parameter estimation errors and the differences in their underlying optimality assumptions (Tu and Zhou, 2010, Kan and Zhou, 2007, and Martellini, Milhau and Tarelli, 2013). Moreover, as the single strategies' performance will show different profiles of dependence on market conditions, a multi-strategy approach can help investors smooth the overall performance across market conditions (Badaoui and Lodh, 2013, Amenc, et al., 2012a).

Exhibit 2 shows that the diversified multi-strategy index has about average outperformance across its constituents with a tracking error of 4.28%, which is below the average tracking error. Consequently, the strategy achieves a very high information ratio of 0.58. Also, its outperformance in bull and bear markets is quite similar, while most other strategies are favored in either bull or bear markets. Overall, diversified multi-strategy exhibits attractive probability of outperformance (> 80%) for the 40-year period. It is a good starting point for investors who are unsure about their capacity either to identify the model with superior assumptions or to take the risk of choosing a particular model in the wrong market conditions.

It is understood that any deviation from cap-weighting will induce systematic risks (as shown in Exhibit 1), but it is misleading to assume that the outperformance of a strategy can be explained simply by these factor premiums alone. In fact, one can still benefit from diversification without taking a particular risk exposure and/or while taking a desired risk exposure. A clear distinction between the stock-selection phase and the weighting phase allows management of implicit factor tilts that may arise from the weighting scheme through an explicit choice of the universe in which the strategy invests (Amenc, et al., 2012b).

Exhibit 3 shows the performance of the diversified multi-strategy index on half universes characterized by high and low market cap, volatility, dividend yield, B/M ratio (value), and liquidity. Since each stock selection corresponds to a factor tilt, these indexes can be considered long-only investible

EXHIBIT 2

Overview of Diversification Strategies

The analysis is based on daily total returns from 12/31/1972 to 12/31/2012 (40 years). The regression coefficients statistically significant at the 95% level are in boldface. The market factor is the daily return of the cap-weighted index of all stocks that constitute the index portfolio in excess of the risk-free rate. The small size factor is obtained from Kenneth French's data library. The value (momentum) factor is the daily return series of a cap-weighted portfolio that is long the 30% highest and short the 30% lowest B/M ratio (past 1 year return) stocks in the CRSP S&P 500 universe. Secondary Market U.S. Treasury Bills (3M) is the risk-free rate in U.S. Dollars. Turnover is mean annual 1-way. All statistics are annualized.

	Max Deconcentration	Max Decorrelation	Efficient Min Vol	Efficient Max Sharpe	Diversified Risk Parity	Diversified Multi-strategy
Ann. Relative Returns	2.39%	2.42%	2.46%	2.69%	2.45%	2.50%
Tracking Error	4.32%	4.36%	5.29%	4.54%	4.23%	4.28%
Information Ratio	0.55	0.55	0.46	0.59	0.58	0.58
Outperf Prob (3Y)	72.3%	79.0%	79.6%	79.9%	76.3%	78.6%
Outperf Prob (5Y)	78.3%	82.1%	79.9%	83.5%	80.6%	81.4%
Max Relative DD	30.07%	30.00%	40.10%	30.66%	34.10%	32.89%
Excess Ret (Bull)	4.3%	3.3%	-0.1%	2.3%	3.2%	2.6%
Excess Ret (Bear)	-0.1%	1.2%	5.4%	2.9%	1.4%	2.1%
TE (Bull)	3.8%	3.9%	4.5%	3.9%	3.7%	3.7%
TE (Bear)	5.1%	5.2%	6.6%	5.7%	5.2%	5.3%

[17] $GLR = \frac{Var(R_P)}{\sum_{i=1}^{N} w_i Var(R_i)}$ where N is the number of stocks in the portfolio, is the return of the portfolio, is the weight of stock and is the return of stock .

[18] Weighted Average Cap of index i = $\sum_{k=1}^{N} W_{k,i}$ Market Cap_k where $W_{k,i}$ is the weight of stock k in index 1, N is the total number of stocks in the index, and Market Cap_k is the float-adjusted market cap of stock k.

proxies of smart-factor indexes. All smart-factor indexes outperform the cap-weighted benchmark in terms of annual returns and Sharpe ratio. The outperformance for well-known risk factors such as high value and low size is more than 4% Investors with capacity constraints can select the indexes like high liquidity and large cap diversified multi-strategy to outperform the benchmark. The turnover of smart-factor indexes is a bit higher than the no-selection index but they stay within the limit of 30%.

The diversification strategy indexes address the limitations of cap-weighted indexes, such as their high concentration levels (in weight or risk contributions) or inefficient return-to-risk profiles. The achievement of the respective objectives is robust over the long term, i.e., across different market conditions. The 3-year probability of outperformance is around 80% for no selection indexes in the long term. Although each strategy has its own benefits, it also has certain limitations that stem from its specific risks. Investors can diversify the strategy-specific risk by allocating across strategies in the form of a diversified multi-strategy index. Finally, value can always be added through diversification, even for a restricted characteristics-based stock selection. ~

Modern portfolio theory (MPT) states that investors should allocate their wealth between a tangency portfolio, or a maximum Sharpe ratio (MSR) portfolio, and a riskless asset.

EXHIBIT 3

Factor-tilted Indexes

The analysis is based on daily total returns from 2/31/1972 to 12/31/2012 (40 years). The benchmark is the cap-weighted index on the CRSP S&P 500 universe. The regression coefficients statistically significant at the 95% level are in boldface. Secondary Market U.S. Treasury Bills (3M) is the risk-free rate in U.S. Dollars. Turnover is mean annual 1-way. All statistics are annualized.

	Diversified Multi-strategy									
	Large Cap	Mid Cap	High Vol	Low Vol	High DY	Low DY	Value	Growth	High Liq	Mid Liq
Ann. Relative Returns	1.50%	4.45%	2.35%	2.90%	3.85%	1.09%	4.85%	0.87%	1.46%	4.25%
Ann. Volatility	16.25%	16.73%	19.54%	14.39%	15.10%	18.12%	16.54%	16.42%	17.23%	15.60%
Sharpe Ratio	0.35	0.52	0.34	0.50	0.54	0.29	0.55	0.31	0.33	0.54
Tracking Error	3.31%	6.80%	6.10%	6.17%	6.24%	4.84%	5.81%	4.07%	2.99%	7.03%
Information Ratio	0.45	0.66	0.39	0.47	0.62	0.23	0.83	0.21	0.49	0.61
Ann. Alpha	**1.01%**	**2.46%**	0.33%	**2.55%**	**2.49%**	0.39%	**2.28%**	0.98%	**0.81%**	**2.57%**
Market Beta	**0.92**	**0.93**	**1.12**	**0.78**	**0.81**	**1.04**	**0.91**	**0.94**	**0.98**	**0.85**
Small Size Beta	**0.06**	**0.32**	**0.36**	**0.03**	**0.07**	**0.28**	**0.17**	**0.18**	**0.11**	**0.25**
Value Beta	**0.08**	**0.16**	**0.07**	**0.14**	**0.25**	**-0.05**	**0.30**	**-0.07**	**0.05**	**0.18**
MOM Beta	**-0.01**	0.00	0.00	0.00	**-0.01**	0.00	**0.01**	**-0.01**	**-0.02**	**0.01**
Capacity (m$)	18 838	2 735	8 732	13 671	12 834	10 174	8 148	14 728	18 997	3 338
1-Way Turnover	21.54%	22.25%	24.92%	24.13%	20.56%	23.42%	28.10%	21.99%	21.62%	21.54%

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