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Research for Institutional Money Management

EDHEC-RISK Institute

INTRODUCTION

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It is my pleasure to introduce the November 2015 edition of the EDHEC-Risk Institute "Research for Institutional Money Management" supplement in partnership with Pensions & Investments (P&I): an infrastructure investing special. Our aim with this supplement is to provide institutional investors with academic insights that are not only relevant but also of practical use from a professional perspective.

Our first article argues that a number of characteristics associated with the structuring of capital projects constitute a much more powerful framework to understand, benchmark and predict long-term returns in infrastructure debt or equity. Thus, infrastructure investment can be construed as a way to buy claims on future cash flows created by long-term contractual arrangements between parties. In numerous cases, infrastructure investors do not actually own any steel or concrete. When they do, the value of their investment is conditioned not by the tangible nature of the asset, but in a license to operate a natural but regulated monopoly.

In the area of infrastructure investment, having progressed towards clear definitions of underlying assets, and built robust, state-of-the-art pricing and risk models that avoid the pitfalls of existing practices and are designed to deliver the answers needed by investors, regulators and policy-makers, it is now time to collect the relevant information. Collecting this information requires large-scale cooperation between investors, creditors, academic researchers and the regulators that can help make such reporting part of a new standard approach to long-term investment in infrastructure by institutional players.

We discuss a dedicated valuation framework for privately-held infrastructure equity investments. Following the roadmap to create long-term infrastructure investment benchmarks that we had previously developed, this framework takes into account the challenges of valuing privately-held and seldom-traded infrastructure equity investments, while aiming to design a methodology that can be readily applied given the current state of empirical knowledge and, going forward, at a minimum cost in terms of data collection.

Moving on from infrastructure to the area of "smart beta" equity investing, we address the issue of combining several smart beta strategies, and clarify the conceptual underpinnings and relevant questions arising when considering smart beta index combinations.

We show that on the basis of existing smart factor indexes, allocation between these indexes can allow an investor who wishes to implement a defensive strategy to avoid concentration in a single factor and above all to benefit from the particular properties of volatility and its dissymmetric nature with respect to market conditions, and thereby adjust the portfolio's defensive bias to market conditions.

We find that value, in terms of risk-adjusted relative performance, can be added through allocation across smart factor indexes, for investors with a tracking error budget. The favorable factor tilts generate outperformance and two-fold diversification, one across factors and another across weighting schemes, reducing tracking error. Implementation of an allocation that guarantees a level of market beta equivalent to that of a cap-weighted index allows the benefits of this relative risk diversification to be optimized.

We show that factor concentration has led many factor indexes to hold Volkswagen AG, and more globally automobile stocks, in large quantities, and ultimately to incur losses in the month of September 2015. Conversely, Scientific Beta's multi-smart-factor indexes, through their construction philosophy, which distinguishes the choice of factor exposures from the implementation of a diversification method, do not suffer from this difficulty.

Recent research suggests that the expected skewness of an asset's returns influences investment decisions. Several empirical studies confirm that investors have preferences for assets whose returns are positively skewed and shy away from assets whose returns are negatively skewed. While this pattern is well documented in the equity market literature, we provide an empirical investigation of the profitability of skewness trading in commodity futures markets.

We would like to extend our warm thanks to our friends at *P&I* for their continuing commitment to the Research for Institutional Money Management supplement, which enables us to maintain our mission of bridging the gap between academic research and professional practice. We wish you an enjoyable and informative read.

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Infrastructure: Shifting the Long-Term Investment Paradigm

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Pension funds and insurers discovered infrastructure investing, somewhat counter-intuitively, around the same time that they began adopting the principles of factor investing. Thus, the schizophrenic search for an infrastructure "asset class" started just as other asset classes were being gradually rejected as unreliable portfolio building blocks.

The objective of seeking exposures to investment factors, which can sometimes seem like the post-modern deconstruction of asset management, really amounts to the search for a well-specified model of asset returns, without missing variables or hidden collinearity. It is the recognition that taxonomies that are not built to correspond to an underlying value process can lead risk management astray if assets are given similar labels when their performance is driven by fundamentally different forces, or vice-versa. Thus, notional grouping of assets (stocks, bonds, private equity, etc.) can sometimes create little information or predictive power. Instead, as is well documented in the financial literature, focusing on a series of systematically rewarded risk factors can allow investors to improve risk-adjusted performance considerably by improving the diversification of both unrewarded and rewarded risks.

Such improvements spring from the discovery of persistent effects in the cross-section of asset prices (also known as factors), often based on economic intuitions and better explanations and predictions of returns than asset class labels.

What are the implications of these evolutions for long-term investment in infrastructure? Is there a point in looking for an "infrastructure asset class"?

Intuitively, infrastructure corresponds to large structures of steel and concrete created to perform a series of industrial functions (water and power supply, transportation, etc.) and is typically labeled following such functional classifications.

But a clear distinction must be made between infrastructure as a matter of public policy, in which case the focus is rightly on industrial functions, and the point of view of financial investors, who may be exposed to completely different risks through investments in firms providing exactly the same industrial functions (e.g. a real toll road and an "availability payment" road[1]).

Hence, the sector classification or "reality" of infrastructure investments constitutes a poor model of the determinants of future cash flows, whether they accrue to equity or debt investors, as a series of EDHEC-Risk Institute papers has now documented (see Blanc-Brude 2013; Blanc-Brude and Ismail 2013; Blanc-Brude, Wilde, and Whittaker 2015 for a discussion and quantitative analyses).

Instead, we argue that a number of characteristics associated with **the structuring of capital projects involving highly relationship-specific assets, that can only be repaid over multiple decades of effective use,** constitute a much more powerful framework to understand, benchmark and predict long-term returns in infrastructure debt or equity.

Thus, infrastructure investment can be construed as a way to buy claims on future cash flows created by long-term contractual arrangements between public and private parties (or alternatively between two private parties). Indeed, in numerous cases, infrastructure investors do not actually own any steel or concrete, which must remain part of the eminent domain of the State. When they do (e.g. certain privatized utilities) the value of their investment is conditioned not by the tangible nature of the asset, but in a license to operate a natural but regulated monopoly.

To help investors achieve long-term goals through asset allocations to infrastructure, two important methodological leaps are now needed.

First, we must recognize that the notion of "infrastructure" is only a **heuristic device** used to access something that investors really want i.e. a mental short-cut designed to create exposure to certain factors, but neither a thing nor an end in itself.

If holding infrastructure debt and equity can give investors access to cash flow processes that have useful characteristics from an asset allocation or from a liability-driven investment perspective, our focus should be on identifying and measuring these characteristics and on designing the relevant investment strategies.

In this respect, substantial progress has been made towards identifying the characteristics that can be expected to systematically explain the financial performance of infrastructure investments. In particular, the growing consensus around the limited role of industrial sector categories in explaining and predicting performance, and the much more significant role played by contracts and by different infrastructure "business models" such as "merchant" or "contracted" infrastructure (see Blanc-Brude, Hasan, and Ismail 2014 for examples), or different forms of utility regulation, is encouraging.

We return to this point in the following article on the collection of standardized investment data for infrastructure investments.

The second important evolution with respect to long-term investment in infrastructure is the transition from a heuristic to a **learning process.**

Indeed, it is not sufficient for long-term capital to be "patient" or to show "persistence through periods of short-term under-performance" (FCTL 2015 p: 6).

Investment factors should be persistent, but long-term investors may not know enough about them today to decide whether they themselves ought to be. Moreover, there may never be enough representative historical data about infrastructure investment to build a robust model of expected performance encompassing the next 50 years (see Blanc-Brude 2014 for a detailed discussion).

The possibility of **learning** should thus become an integral part of the approach taken by long-term investors to make and adapt long-term investment decisions, in particular with regards to sequential investments such as infrastructure. The higher monitoring demand that comes with buy-and hold strategies can be combined with inference techniques designed to revise or update prior assessments of value and performance, as and when new data becomes available.

For instance, Blanc-Brude and Hasan (2015) show that while it is difficult to empirically document the cash flow dynamics of infrastructure projects spanning multiple decades, we can optimize the use of available information by integrating what we know today about different types of financial structuring decisions and contractual terms found in infrastructure investments, to build models of expected cash flows and conditional volatility that can be calibrated and improved with the data that does exist.

Furthermore, once the relevant data to update pricing and risk models has been identified, the standardization of its collection becomes possible, as we discuss in a recent EDHEC-Risk paper (Blanc-Brude et al. 2015), which proposes a data collection template for the creation of infrastructure investment benchmarks.

The combination of a reporting framework with a central database of infrastructure project information and monitoring and valuation frameworks that are built to integrate new information as it becomes available, which EDHEC has been developing, will allow investors to improve and adapt their long-term investment decisions with regards to infrastructure. Both aspects are covered in the following two articles.

In conclusion, if infrastructure investing is to come of age and become fully integrated in the asset allocation and asset-liability management of investors, a change of focus is required from the same investors and most of the managers that provide them with access to infrastructure assets.

This new focus should be on collecting the kind of information that can help answer the questions that investors (and their regulators) actually have about performance and risk.

With the new data collection template defined by EDHEC, which has been designed to correspond to the requirements of the relevant asset pricing and risk models, a rationale exists to collect data effectively and efficiently to build infrastructure investment benchmarks.

Collecting this information now requires large-scale cooperation between investors, creditors, academic researchers and the regulators that can help make such reporting part of a new standard approach to long-term investment in infrastructure by institutional players. •

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[1] *Real toll roads charge user fees as a function of effective traffic, whereas "availability payment" projects receive a fixed compensation from the public sector in exchange for the construction, operations and maintenance of a road according to a pre-agreed output specification.*

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Setting the Standard for Data Collection and Reporting in Private Infrastructure Investments

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In recent years, frequent calls have been made in policy fora for data collection efforts to be stepped up with respect to infrastructure investment, but it is often unclear which data should be collected, to achieve what end, and how.

In a new paper (Blanc-Brude et al. 2015), we propose a template for collecting and reporting infrastructure investment data for the purpose of building investment benchmarks corresponding to reference portfolios of privately-held infrastructure debt or equity.

To establish what data needs to be collected, we start from the reasons why infrastructure investment benchmarks are in demand and list the key questions that such benchmarks should be expected to answer.

What are the relevant questions?

- Asset allocation: documenting the risk-adjusted performance of infrastructure investments compared to other public or private assets includes deriving measures of **expected and realized returns, return volatility and of the correlation of these returns** with the market. This determines whether there is such a thing as an infrastructure "asset class" that could improve existing asset allocation policies, or what combination of investment factors infrastructure debt and equity might correspond to.
- Prudential regulation: The current treatment of privately-held infrastructure is debatable and certainly contradicts the investment beliefs that draw investors to these assets. Without **adequate measures of extreme risks** and calibrations of existing prudential frameworks, institutional investors are less able to invest in infrastructure.
- Liability-driven investment: infrastructure investments may have the potential to contribute to asset-liability management objectives, even if they do not correspond to a well-identified asset class. Different **duration and inflation hedging measures** of infrastructure investments will play a key role in their integration in the asset-liability structure of investors. Arriving at such measures is fully part of the objective to create infrastructure benchmarks.

Why these questions cannot be answered today

The questions are important to the future of infrastructure investment by long-term investors, in particular investors with a liability profile and subjected to prudential rules, such as insurance firms. However, the current state of investment knowledge does not allow them to be answered.

- **Market proxies are ineffective:** looking for estimates of expected performance and risk of privately-held infrastructure investments in the market for publicly-traded securities has not delivered meaningful results so far. Listed infrastructure equity and debt indexes tend to exhibit higher risk than broad market indexes (higher maximum drawdown, higher VaR) partly because they are highly concentrated in a few large constituents. Crucially, they do not suggest any persistent improvement in investors' existing portfolios (see Blanc-Brude 2013; Blanc-Brude, Wilde, and Whittaker 2015 for a review and quantitative analysis).
- **Existing research using private data is too limited:** existing sources and studies on the performance of infrastructure PE funds suffer from major limitations and cannot be considered representative of the performance of underlying assets. In fact, it is because infrastructure PE funds are not representative that a number of large asset owners have gradually opted to invest directly in infrastructure. Likewise on the debt side, information available from rating agencies about infrastructure debt, while much richer, is insufficient to answer questions about the performance, extreme risk and effective duration of reference portfolios of private infrastructure debt.
- **Reported metrics are inadequate:** the metrics currently reported in infrastructure investment are also not fit for purpose. Appraisal-based net asset values (NAVs) suffer from the usual stale pricing issues which lead to smoothing and underestimating the volatility of returns, and the use of constant internal rates of return (IRRs) precludes building portfolio measures, identifying sources of return (factors) or computing the correct duration measures with risk profiles that are expected to change over time, which is the case with infrastructure projects.

Recent progress: from definitions to data collection

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

A number of the recommended steps have now been taken and the framework required to define and launch the data collection process now exists. Defining infrastructure investments from a financial perspective, the only relevant perspective to build investment benchmarks, was a necessary first step.

A clear distinction had to be made between infrastructure as a matter of public policy, in which case the focus is rightly on industrial functions (water supply, transportation, etc.) and that of financial investors who may be exposed to completely different risks through investments in firms providing exactly the same industrial functions (e.g. a real toll road and an "availability payment" road[2]).

Substantial progress has been made towards identifying those characteristics that can be expected to systematically explain the financial performance of infrastructure investments. In particular, the growing consensus around the limited role of industrial sector categories in explaining and predicting performance, and the much more significant role played by contracts and by different infrastructure "business models" such as "merchant" or "contracted" infrastructure, or different forms of utility regulation, is encouraging.

A first result has been the identification of limited-recourse project finance as a major and well-defined form of investment structuring for infrastructure projects. Benchmarking project finance debt and equity by broad categories of concession contracts, financial structures and life-cycle stage is one approach to creating reference portfolios that can be used as benchmarks, including for prudential regulation as

> To establish what data needs to be collected, we start from the reasons why infrastructure investment benchmarks are in demand.

[2] *A road project company receiving a fixed compensation from the public sector in exchange for the delivery of the construction, operations and maintenance of a road up to a pre-agreed output specification.*

the recent EIOPA consultations suggest.[3]

In due course, other approaches can complement this first step to integrate other types of underlying infrastructure business models (e.g. "RPI-X" vs. "rate of return" utility regulation) in a broader benchmarking exercise of privately-held infrastructure investments.

With the financial instruments corresponding to infrastructure investment usefully defined, the second necessary step was to design a performance and risk measurement framework that can provide robust answers to the questions identified above.

Privately-held infrastructure equity and debt instruments are not traded frequently and cannot be expected to be fully "spanned" by a combination of public securities. Hence, they are unlikely to have unique prices that all investors concur with at one point in time. A two-step approach to measuring performance is therefore necessary:

1. Documenting the statistical distributions (mean and variance) of debt service and dividends in order to address the fundamental problem of unreliable or insufficiently reported NAVs or losses given default (LGDs);
2. Estimating the relevant (term structure of) discount rates, or required rates of returns, and their evolution in time. Here too, progress has been made and recent EDHEC research provides a framework addressing both steps, taking into account the availability of data, while applying best-in-class models of financial performance measurement.

The result is a list of data items required to implement adequate methodologies and answer the right questions. This list includes "base case" and revised cash flow forecasts for equity and debt investors, as well as realized debt service and dividends, and key financial ratios, in particular debt service and equity service cover ratios, and their determinants. Finally, modeling cash flows requires knowledge of loan covenants and expected and realized investment milestones.

Once the expected value and volatility of cash flows to creditors and investors is known, as best as current information allows, the relevant term structure of discount rates can be estimated to derive past and forward-looking measures of performance, risk and liability-hedging.

Starting from a distribution of cash flows, several approaches are available, such as factor extraction from initial investment values, following Ang et al. (2013). Blanc-Brude and Hasan (2015) provide an application to infrastructure project equity, which is detailed in a separate article in this supplement: A New Framework for the Valuation of Privately-Held Infrastructure Equity.

A second option is the risk-neutral valuation approach described in Kealhofer (2003). Blanc-Brude, Hasan, and Ismail (2014) provide an application to private infrastructure debt that integrates the Black and Cox (1976) extension of the Merton (1974) structural model, and allows for debt restructuring post-default, hence valuing the option available to infrastructure lenders to restructure project debt.

Implementing these methods requires collection of a set of data items, including initial investment values and credit spreads, all of which are observable.

The detailed list of the required data items is presented in Blanc-Brude et al. (2015).

The need for cooperation

Having progressed towards clear definitions of underlying assets, and built robust, state-of-the-art pricing and risk models that avoid the pitfalls of existing practices (e.g. averaging IRRs) and are designed to deliver the answers needed by investors, regulator and policy-makers, it is now time to collect the relevant information.

With the data collection template defined by EDHEC, which has been designed to correspond to the requirements of the relevant asset pricing and risk models, a rationale exists to collect data effectively and efficiently to build infrastructure investment benchmarks.

Collecting this information now requires large-scale cooperation between investors, creditors, academic researchers and the regulators that can help make such reporting part of a new standard approach to long-term investment in infrastructure by institutional players.

This work is ongoing at EDHEC and benefits from the support of numerous private sector organizations including long-standing research sponsors such as NATIXIS, Meridiam and Campbell Lutyens, as well as the members of the Long-Term Infrastructure Investor Association. •

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[3] *See https://eiopa.europa.eu/regulation-supervision/insurance/investment-in-infrastructure-projects*

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A New Framework for the Valuation of Privately-Held Infrastructure Equity

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In a new paper drawn from the Meridiam/Campbell Lutyens research chair at EDHEC-Risk Institute, we propose a dedicated valuation framework for privately-held infrastructure equity investments.

Following the roadmap to create long-term infrastructure investment benchmarks described in Blanc-Brude (2014), this framework takes into account the challenges of valuing privately-held and seldom-traded infrastructure equity investments, while aiming to design a methodology that can be readily applied given the current state of empirical knowledge and, going forward, at a minimum cost in terms of data collection.

Three challenges

The valuation of unlisted infrastructure project equity stakes requires three significant challenges to be addressed:

- **Endemic data paucity:** while primary and secondary market prices can be observed, sufficiently large and periodic samples, representative of different types of infrastructure projects at each point in their multi-decade lifecycle are unlikely to be available every year in each regional market.
- **The term structure of expected returns:** the nature of such investments requires estimation of a term structure of discount factors at different points in their lives that reflects the change in their risk profile. Indeed, in expectation, infrastructure investments can exhibit a dynamic risk profile resulting from the sequential resolution of uncertainty, including the frequent de-leveraging of the project company's balance sheet.
- **The absence of a unique price** for a given investment in unlisted infrastructure, which springs from the fact that there is no direct traded equivalent to the payoff of infrastructure project equity. It follows that prices are partly driven by investor preferences and that substantial bid/ask spreads are likely.

The first point is partly a mundane aspect of the difficulties encountered when collecting data on private investments, but also a reflection of the nature of long-term equity investment in infrastructure. The type of infrastructure projects that have been financed in the past are not necessarily representative of investment opportunities today. Thus, even if year-23 dividends for projects that were financed 24 years ago can be observed today, they may not be good predictors of dividends in projects financed 3 years ago, 20 years from now. For example, projects financed in the early 1990s may have been in sectors where fewer projects exist today (e.g. telecoms) or rely on contractual structures or technologies that are not relevant to long-term investors in infrastructure today (e.g. coal-fired merchant power).

Data paucity is an endemic dimension of the valuation of privately-held infrastructure equity investments i.e. we must start from the premise that we cannot observe enough data to simply derive prices empirically. Instead, we acknowledge a position of relative ignorance and aim to build into our approach the possibility to improve our knowledge as new cash flow and transaction data that can be used to update models of dividend distributions and asset pricing become observable.

The second point about the term structure of expected returns has long been made in the finance literature: using constant and deterministic discount rates is defective if projects have multiple phases and project risk changes over time as real-options are exercised by asset owners.

It also amounts to assuming that the risk-free rate, asset beta, and market risk premium are constant and deterministic, when we know that such variables are time-varying and stochastic. Moreover, the internal rate of return (IRR) of individual investments cannot be easily used to estimate performance at the portfolio level, as the IRR of a portfolio is not the same as the weighted-average IRRs of individual investments.

Thus, using methodologies based on discounting at a constant rate, while common in the corporate sector, is inadequate for the purposes of long-term investors, who need performance measures that can help them make hedging, risk management, and portfolio management decisions.

The third point (the absence of unique pricing measures) is a reflection of what is usually labeled 'incomplete markets' i.e. the fact that the same asset can be valued differently by two investors, and yet this does not constitute an arbitrage opportunity (and therefore the bid-ask spread does not narrow) because transaction costs are high and because, in the absence of complete markets, investor preferences partly explain prices.

The existence of a range of (or bounds on) values is also impacted by market dynamics: if a new type of investor (e.g. less risk averse) enters the private infrastructure equity market, the range of observable valuations for similar assets may change. Likewise, if some investors want to increase their allocations to unlisted assets, given the limited available stock of investable infrastructure projects at a given point in time, their valuations may rise, but not those of others (who may sell).

Hence, the important point is that the required rate of return or discount rate of individual investors' infrastructure equity is fundamentally unobservable: it cannot be inferred from observable transaction prices since it is both a function of the characteristics of the asset (e.g. cash flow volatility) and individual investor preferences.

Improving existing valuation methods

Because of these challenges, existing approaches developed to value private equity investments are mostly inadequate for the purpose of valuing unlisted infrastructure project equity.

In our review of the literature we identify three groups of valuation techniques: repeat sales, public market equivalents and factor extraction from cash flows. Importantly, these techniques all imply that enough data can be observed to compute a price.

The repeat sales approach assumes that asset betas can be inferred from discrete and unevenly timed transaction observations after correcting for price staleness and sampling bias, while the public market equivalent approach implies that public asset betas can be combined to proxy the return of unlisted assets. Cash flow-driven approaches are less normative and aim to derive the unobservable rate of return of unlisted assets by decomposing their implied returns into traded and untraded components ex post facto, that is, once all cash flows have been observed and can be related to equally observable market factors.

Thus, these approaches cannot be directly applied to privately-held infrastructure investments, the value of which is determined by streams of expected and risky cash flows that mostly occur in the future, and for which few comparable realized investments exist today.

Existing approaches also typically fail to take into account the subjective dimension of asset pricing in the unlisted space and compute asset betas and alphas as if a unique pricing measure existed i.e. as if all investors had similar preferences, and in some papers, as if private equity exposures could always be replicated with a combination of traded assets.

Deriving discount factors endogenously

To the extent that infrastructure dividend cash flows can only be partially observed today, their expected values cannot be decomposed into exogenous factors (markets, the economy, etc.), the future value of which is not known today and would be very perilous to predict 30 years from now.

Instead, we must derive the relevant discount factors endogenously i.e. using observable information about each private investment in infrastructure equity including, as suggested above, its contractual characteristics, location, financial structure, etc., as well as the value of the initial equity investment made, which is also observable.

Hence, we argue that a robust valuation framework for equity investments that solely create rights to future (and yet largely unobserved) risky cash flows, as is the case of privately-held infrastructure equity, requires two components:
1. A model of expected dividends and conditional dividend volatility, calibrated to the best of our current knowledge;
2. A model of endogenously determined discount factors, that is, the combination of expected returns implied by the distribution of future dividends, given observable investment values.

In other words, as for any other stock, the valuation of privately-held equity in infrastructure projects amounts to deriving the appropriate discount rates for a given estimate of future dividends. But while this process is implicit in the pricing mechanism of public stock markets, in the case of privately-held equity with distant payoffs, we have to derive the relevant parameters explicitly, taking into account the characteristics of infrastructure assets.

Dividend distribution model and required data

The dividend stream or cash flow process can be described as state-dependent and we introduce a new metric for infrastructure project dividends: the equity service cover ratio or ESCR, which is computed as the ratio of realized-to-base case dividends.

The base case equity forecast of infrastructure equity investments, while not necessarily accurate, provides a useful and observable quantity, which by definition spans the entire life of each investment. Thus, we propose to describe the behavior of equity cash flows in infrastructure projects as a function of this initial forecast, in order to create metrics that allow direct comparisons between different equity investments.

In our paper, we show that the value of the ESCR at each point in the lifecycle of infrastructure equity investments can be used as a state variable describing the dynamics of the cash flow process. In combination with a given project's base case dividend forecast (which is known at the time of investment), knowledge of the distribution of the ESCR at each point in time is sufficient to express the expected value and conditional volatility of dividends.

The fact that new observations are not redundant today (we can still learn about the dynamics of dividends in infrastructure investment by collecting new data), justifies the need for an ongoing and standardized reporting of these cash flows to keep learning about their true distribution and value the infrastructure investments made today, tomorrow.

Filtering implied market values (and their bounds)

Since the term structure of expected returns of individual investors/deals is unobservable and lies within a range (or bounds) embodying market dynamics at a given point in time, we adapt the classic state-space model mostly used in physical and natural sciences to capture the implied average valuation (or state) of the privately-held infrastructure equity market at one point in time and its change from period to period. Using

such a model also allows us to capture the market bounds on value implied by observable investment decisions for a given stream of expected cash flows.

The objective of state-space models is parameter estimation and inference about unobservable variables in dynamic systems, that is, to capture the dynamics of observable data in terms of an unobserved vector, here the term-structure of discount factors. Hence, we have an observation equation relating observable data to a state vector of discount factors, and a state equation, which describes the dynamics of this state, from one observation (transaction) to the next. Each transaction corresponds to a new state i.e. a given term structure of discount factors matching the price paid in that transaction (the initial investment) with expected cash flows, which may or may not be the same as the previous transaction's.

Given a stream of risky future dividends, if the price paid in the current transaction is different from that paid in the previous one, it must be because the valuation state has shifted. The valuation state can change due to a change in investor preferences between the two deals, or due to a change in the consensus risk profile of those kinds of investments (e.g. projects with commercial revenues after a recession), or because of a change in the overall market sentiment (the average) valuation.

Thus, by iterating through transactions, we may derive an implied average valuation state (a term structure of discount factors) and its range, bounded by the highest and lowest bidders in the relevant period.

Later, when dividend payments are realized, period returns can be computed using the discounted sum of remaining cash flows as the end-of-period value (given the implied term structure of discount factors at that point).

In our research, we define the observation equation using a dynamic version of the standard Gordon growth model (discounted dividends) and the state equation using an autoregressive (with a one-period lag) model of the term structure of expected returns, which can be derived from the kind of factor model of expected excess returns that is commonly found in the financial literature. We take the view that expected returns are a function of conditional dividend volatility.

In a simple, linear setting, we show that we can iterate through observable investments, while estimating model parameters on a rolling basis, to capture both the implied expected returns (and discount factors) during a given reporting period and track these values and their range (arbitrage bounds) from period to period.

Illustration

As an illustration of our approach, we apply the dividend and pricing models to a generic case of privately-held infrastructure investment, assuming an expected ESCR and ESCR volatility profile (including the probability of receiving no dividends in any given period).

Given a base case dividend scenario inspired by an actual infrastructure project financed in Europe in the last decade, we obtain a full distribution of future dividends and apply our valuation framework to this assumed dividend process for a (an equally assumed) range of investment values. Some of the key outputs are shown in the following exhibits.

Exhibit 1 shows the resulting filtered term structure of expected period and multi-period (average) expected returns filtered from a range of 20 consecutive initial transactions in this type of project.

Exhibit 2 shows the resulting values of the dividend discount factor[4] at the time of valuation and the expected average price and its range for this group of transactions.

Finally, Exhibit 3 shows how we can implement this model with rolling parameter estimation to track the implied average expected returns and price of consecutive transactions from period to period.[5]

These results spring from model inputs that are only inspired by existing data and a number of intuitions about privately-held infrastructure equity investments, and can only be considered an illustration. However, they show clearly that with well-calibrated cash flow models and a transparent valuation framework, the kind of performance measures that have so far been unavailable to long-term investors can readily be derived and monitored in time, as new investments are made.

Future steps

Next steps include the implementation of our data collection template to create a reporting standard for long-term investors and the ongoing collection of the said data. Beyond, in future research, we propose to develop models of return correlations for unlisted infrastructure assets in order to work towards building portfolios of privately-held infrastructure equity investments. These developments will take place with the support of, and in collaboration with the financial industry and its regulators.

This work continues with the support of Meridiam and Campbell Lutyens, as well as the other members of the Long-Term Infrastructure Investor Association, who are spearheading the standardization and mass collection of data to calibrate the cash flow and pricing models described above. •

EXHIBIT 1

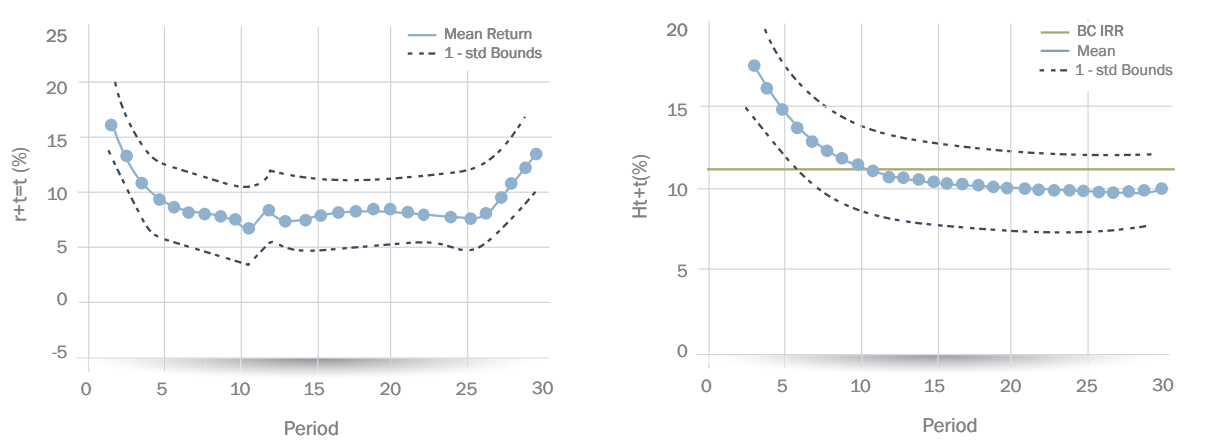


EXHIBIT 2

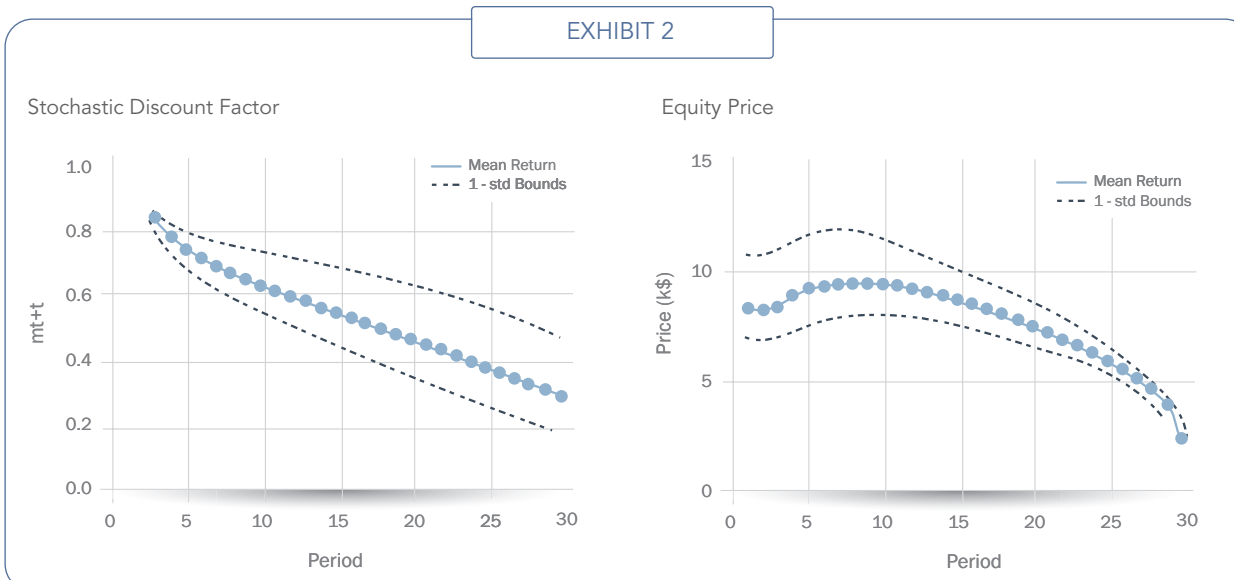
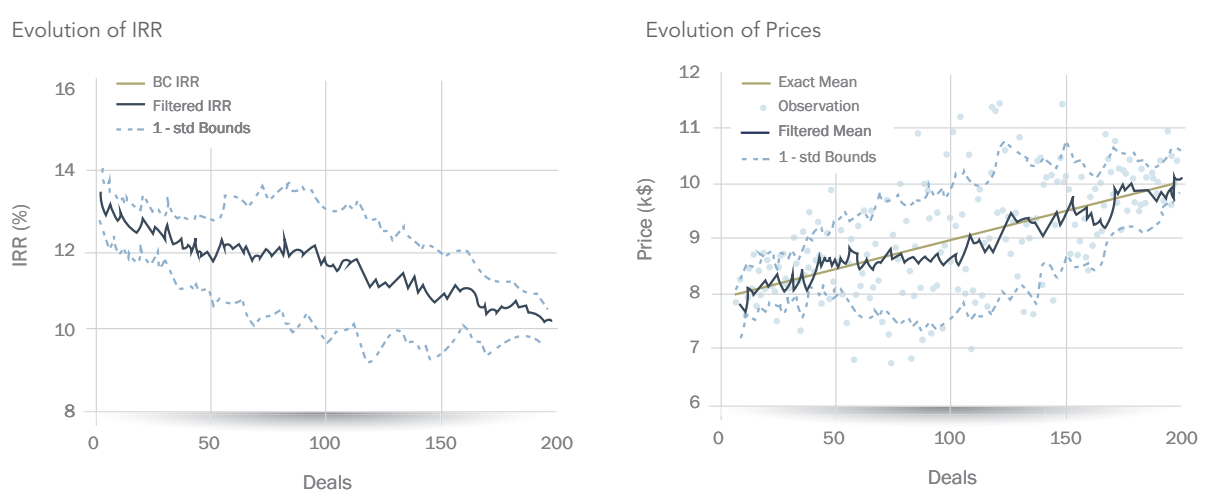


EXHIBIT 3



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Blanc-Brude, F. and M. Hasan. *2015. The Valuation of Privately-Held Infrastructure Equity Investment. EDHEC and Meridiam/Campbell Lutyens research chair on Infrastructure Equity Benchmarking. Singapore: EDHEC-Risk Institute, March.*

[4] *Using continuously compounded (log) returns, the discount factor is simply the exponent of minus the total return from the valuation date until the relevant period.*

[5] *In this example, the average price investors are willing to pay for the same infrastructure asset is assumed to increase continuously (perhaps because investors increasingly value assets that pay predictable dividends in bad states of the world) but the range of prices investors are willing to pay to buy a stake in this (unchanged) dividend process is also assumed to change. Initially it is assumed to widen (say that new investors become active in this market and have different preference or views on risk); half way through the 200 observed transactions, the range of valuations is assumed to start shrinking (perhaps there is now a greater consensus amongst investors about risk or more traded assets allowing replication).*

INDEXES

The General Principles of EDHEC Risk Smart Allocation Offerings

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Smart beta product offerings have proliferated over the past decade, offering investors an ample choice of different factors and different weighting schemes to select from for a relevant smart beta index. However, in addition to the question of selecting a suitable index as a stand-alone investment, the question of combining different smart beta strategies naturally arises in the context of an extensive range of smart beta offerings. This article addresses the issue of combining several smart beta strategies, and clarifies the conceptual underpinnings and relevant questions arising when considering smart beta index combinations.

We first look at the design of efficient and investable proxies for risk premia, and then assess simple combinations of smart beta strategies through naïve diversification, and finally discuss additional potential for value added inherent in customized smart beta allocations.

Designing efficient and investable proxies for risk premia

Current smart beta investment approaches only provide a partial answer to the main shortcomings of capitalization-weighted (cap-weighted) indexes. We discuss a new approach to equity investing referred to as smart factor investing. It provides an assessment of the benefits of simultaneously addressing the two main shortcomings of cap-weighted indexes, namely their undesirable factor exposures and their heavy concentration, by constructing factor indexes that explicitly seek exposures to rewarded risk factors while diversifying away unrewarded risks. Addressing these two points simultaneously is made possible through the Smart Beta 2.0 approach, which combines a stock selection step (to select stocks with the desired factor tilt or characteristics) with a diversification-based weighting scheme. This weighting scheme is applied to the relevant stock selection to obtain a well-diversified portfolio within a given factor tilt. Our results suggest that such smart factor indexes lead to considerable improvements in risk-adjusted performance.

The results in Exhibit 1 confirm that the combination of relevant security selection and appropriate weighting schemes in a two-step process leads to substantial improvements in risk-adjusted performance with respect to the use of a standard cap-weighted index, which typically implies an inefficient set of factor exposures and an excess of unrewarded risk.

On the one hand, starting with a focus on the systematic risk exposure, we find that a higher Sharpe ratio can be achieved with the same weighting scheme, here a cap-weighting scheme, for stocks selected on the basis of their loadings on the value, size, momentum, low volatility, low investment and high profitability factors, compared to the case where the full universe is held in the form of a cap-weighted portfolio.

This finding underlines that these factors carry a long-term premium, and in this sense constitute rewarded risk. In fact, financial researchers have argued that stocks that provide these tilts tend to be exposed to different sources of systematic risk than a broad market index, implying that investors are exposed to a risk of poor returns in bad times when following such strategies. For example, value stocks have been shown to have increasing market betas during recessionary shocks, smaller-size companies have been argued to be exposed to liquidity and distress risk, momentum stocks have been argued to be heavily exposed to negative shocks in expected economic growth, low investment and high profitability stocks reflect a high discount rate for investments and even low volatility stocks have been argued to carry additional risks, in

EXHIBIT 1

Diversifying away unrewarded risks: performance comparison of US cap-weighted factor indexes and US multi-strategy factor indexes.
The analysis is based on daily total return data from 12/31/1974 to 12/31/2014 (40 years). The benchmark used for the relative analytics is the SciBeta CW US 500 index. Mid Cap, High Momentum, Low Volatility, Value, Low Investment and High Profitability selections all represent 50% of stocks with such characteristics in a US universe of 500 stocks. The risk-free rate is the return of the 3-month US Treasury Bill. Maximum relative drawdown is the maximum drawdown of the long-short index whose return is given by the fractional change in the ratio of the strategy index to the benchmark index. The probability of outperformance is the probability of obtaining positive excess returns from investing in the strategy for a period of 1 (or 3) years at any point during the history of the strategy. A rolling window of length 1 (or 3) years and a step size of 1 week is used. The full names of the US indexes used are: SciBeta United States Mid-Cap Diversified Multi-Strategy, SciBeta United States High-Momentum Diversified Multi-Strategy, SciBeta United States Low-Volatility Diversified Multi-Strategy, SciBeta United States Value Diversified Multi-Strategy, SciBeta United States Low-Investment Diversified Multi-Strategy and SciBeta United States High-Profitability Diversified Multi-Strategy. Source: www.scientificbeta.com.

US Long-Term (Dec 1974 - Dec 2014)		Mid Cap		High Momentum		Low Volatility			Value	Low Investment		High Profitablity	
	Broad CW	CW	Diversified Multi-strategy	CW	Diversified Multi-strategy	CW	Diversified Multi-strategy	CW	Diversified Multi-strategy	CW	Diversified Multi-strategy	CW	Diversified Multi-strategy
Ann. Returns	12.16%	15.49%	16.75%	13.10%	15.65%	12.40%	15.03%	13.66%	16.70%	13.96%	16.05%	12.63%	15.49%
Ann. Volatility	17.12%	17.59%	16.57%	17.30%	16.12%	15.50%	14.16%	17.83%	16.37%	15.96%	15.34%	17.06%	15.95%
Sharpe Ratio	0.41	0.59	0.7	0.46	0.65	0.47	0.7	0.48	0.71	0.55	0.71	0.44	0.65
Max Drawdown	54.53%	60.13%	58.11%	48.91%	49.00%	50.50%	50.13%	61.20%	58.41%	53.38%	53.20%	52.29%	48.28%
Ann. Excess Returns	-	3.33%	4.59%	0.94%	3.49%	0.24%	2.87%	1.51%	4.54%	1.80%	3.89%	0.47%	3.33%
Ann. Tracking Error	-	5.75%	6.38%	3.50%	4.72%	4.47%	6.04%	4.53%	5.56%	3.85%	5.44%	3.34%	4.39%
95% Tracking Error	-	9.39%	11.42%	6.84%	8.58%	9.20%	11.53%	8.72%	10.14%	6.89%	10.06%	6.75%	7.58%
Information Ratio	-	0.58	0.72	0.27	0.74	0.05	0.48	0.33	0.82	0.47	0.72	0.14	0.76
Outperformance Probability (1Y)	-	61.69%	67.78%	62.23%	67.24%	49.36%	66.06%	60.27%	70.83%	61.54%	71.86%	51.23%	70.58%
Outperformance Probability (3Y)	-	69.25%	74.38%	78.47%	83.13%	52.85%	76.04%	66.25%	78.73%	75.21%	81.16%	58.59%	82.35%

In practice, investors may thus select among various ways of combining smart factor indexes in order to account for their investment beliefs, objectives and constraints.

the sense that they may suffer during times of liquidity stress.

The results we obtain, reported in Exhibit 1, show that while the Sharpe ratio of the broad cap-weighted index is 0.41 on the sample period, it is considerably improved by a cap-weighted strategy using a stock selection to tilt towards rewarded factors[6]. These results suggest that a systematic attempt to harvest equity risk premia above and beyond broad market exposure leads to additional risk-adjusted performance.

The results we obtain, reported in Exhibit 1, show that while the Sharpe ratio of the broad cap-weighted index is 0.41 on the sample period, it is considerably improved by a cap-weighted strategy using a stock selection to tilt towards rewarded factors . These results suggest that a systematic attempt to harvest equity risk premia above and beyond broad market exposure leads to additional risk-adjusted performance.

On the other hand, shifting to the management of specific risk exposures, we find that even higher levels of Sharpe ratio can be achieved for each selected factor exposure through the use of a well-diversified weighting scheme, which we take to be an equally-weighted combination of five popular smart weighting schemes[7] that enable the unrewarded or specific risk of each smart factor index to be reduced.

The category of specific risks corresponds to all the risks that are unrewarded in the long run, and therefore not ultimately desired by the investor, but that can have a strong influence on either the volatility and the maximum absolute drawdown of the index, or the tracking error or maximum relative drawdown of the index. 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 unrewarded financial risk factors. The academic literature considers, for example, that commodity, currency and 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 unrewarded financial risks, we also find specific financial risks (also called idiosyncratic stock risks) which correspond to the risks that are specific to the company itself (its management, the risk of 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 knowing, evaluating and choosing in order to create alpha, but portfolio 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 weighting scheme reduces the quantity of unrewarded risk, whether it involves unrewarded risk factors or unrewarded specific financial risks. However, like any model, it is imperfect and can itself lead to non-negligible residual exposures to certain unrewarded risks. This imperfection stems from the fact that the methodologies used seldom lead to an optimal and unique Maximum Sharpe Ratio portfolio as in Modern Portfolio Theory, whether it is a question of having accepted ex ante not to seek it (optimality risk), or to establish ex post the distance for a portfolio that would not be subject to parameter estimation errors. For example, minimum volatility portfolios, which are robust proxies for efficient portfolios, and therefore well diversified, are nonetheless not optimal portfolios ex ante since they do not target the maximum Sharpe ratio except if one considers that all stocks have the same return. De facto, efficient minimum volatility portfolios are often exposed to significant sector biases. Naturally, ERI Scientific Beta always tries to implement diversification models that are the least exposed possible to these unrewarded risks. For example, the use of norm constraints is a good compromise between the desire to fully utilize the potential to reduce the volatility in an efficient way procured by a minimum-volatility-type weighting scheme, while avoiding over-concentration in a small number of low-volatility stocks.

Specific or unrewarded risks can also correspond to operational or non-financial risks that are specific to the implementation of the diversification model. As such, for example, a maximum decorrelation scheme depends on a good estimation of the correlation matrix to ensure robust diversification. As part of the quality assurance for these indexes, ERI Scientific Beta attaches a high price to the technical quality of the models used and their implementation to reduce this type of specific risk (for example, our research on the estimation of correlation matrices is part of this approach). In spite of all the attention paid to the quality of model selection and the implementation methods for these models, this specific operational risk, like the unrewarded financial risks described above, remains present nonetheless and it therefore seems interesting to be able to reduce even further the exposures that each weighting scheme, even if it is smart, is not able to diversify. This is the objective of the diversified multi-strategy approach.

Thus, the Sharpe ratio of the diversified multi-strategy indexes reaches even higher levels of risk-adjusted return (Sharpe ratio) than cap-weighted tilted indexes for the same factors.

These results suggest that multi-strategy factor-tilted indexes obtain the desired factor tilts without undue concentration, which provides an explanation for their superior risk-adjusted performance with respect to the cap-weighted combination of the same selection of stocks.

Overall, it appears that the combined effects of a rewarded factor exposure ensured by a proper dedicated security selection process and efficient harvesting of the associated premium through improved portfolio diversification leads to considerable Sharpe ratio improvements compared to the broad cap-weighted index.

In a nutshell, an improved weighting scheme which focuses on diversification such as diversified multi-strategy weighting allows unrewarded risks to be diversified away. This reduction of unrewarded risk through diversification is at the heart of the Smart Beta 2.0 approach advocated by Scientific Beta.

Obtaining a well-diversified index within each factor tilt is at the core of the improved performance of these indexes. However, one may expect further benefits by allocating across different factor premia rather than focusing on a single factor tilt, notably because the academic literature and empirical research show that there is a good level of decorrelation for the risk premia associated with these factors. This allocation across different rewarded factors is at the heart of multi-smart-beta-allocation approaches, which we turn to below.

Combining multiple factors

Below, we look at Scientific Beta Multi-Beta Multi-Strategy (Equal-Weighted) indexes as an example of combining different factor indexes. This index provides simple access to smart beta allocation by simply combining the different factor-tilted indexes in equal proportions. For a long-term US track record (1974-2014) this index produces annual outperformance over a broad cap-weighted index of 3.95%. The index has been live since December 20, 2013 and has confirmed this performance with live annual outperformance of 1.47% as of June 30, 2015[8].

The index draws on the diversified multi-strategy indexes for four factor tilts presented in Exhibit 1 above, namely the value, low volatility, small size, and momentum tilts. These four factor-tilted indexes represent access to different rewarded risk factors. Combining exposures to these four factors provides access to the associated rewards, but the simple equal-weighted allocation does not account for any particular objective in terms of management of absolute or relative risk objectives and in this sense constitutes a naive form of factor allocation. In particular, equal-weighted allocation does not account for differences in correlations across the different pairs of factor indexes that are being combined, nor does it consider differences in volatility across the different component indexes. This naive diversification across factors is nevertheless a starting point for the use of the relative return correlations documented in Exhibit 2, which logically allows the risk to be reduced for a level of return that is the average of the returns of the various smart factor indexes, and therefore improves the information ratio compared to the average information ratio of the indexes.

Naturally, a less naive form of diversification across smart

[6] *The cap-weighted tilted strategies are implemented by selecting on a quarterly basis the top 50% of stocks in the reference universe by the relevant factor score (i.e. the 50% of stocks with respectively the lowest market cap, highest book-to-market, highest past returns, or the lowest volatility) and weighting them in proportion to their free-float adjusted market cap.*

[7] *Diversified Multi-Strategy weighting is an equal-weighted combination of the following five weighting schemes – Maximum Deconcentration, Diversified Risk Weighted, Maximum Decorrelation, Efficient Minimum Volatility and Efficient Maximum Sharpe Ratio. Maximum Deconcentration consists of maximizing the effective number of stocks subject to turnover and liquidity constraints and thus corresponds to an adjusted version of equal-weighting. Diversified Risk Weighted attributes stocks weights inversely proportional to their volatility. Maximum Decorrelation constructs a portfolio of stocks that behave differently over time, which is achieved by minimizing portfolio volatility subject to the assumption that volatility is identical across stocks. Efficient Minimum Volatility consists of volatility minimization subject to norm constraints. Efficient Maximum Sharpe ratio maximizes the Sharpe ratio of the portfolio given the assumption that expected returns are proportional to the median semi-deviation of stocks in the same decile resulting from a sort on stock-level semi-deviation. The three latter strategies require a covariance matrix as an input to the optimization problem. The covariance matrix is estimated using a robust estimation procedure employing a statistical factor model based on principal component analysis where the number of components is selected using a criterion from random matrix theory. For more details on the weighting schemes and the derivation of required input parameters, see www.scientificbeta.com).*

[8] *Annual relative return of the Scientific Beta USA Multi-Beta Multi-Strategy EW index over the period from 20/12/2013 to 30/06/2015, using the Scientific Beta broad CW index as the reference index.*

factor indexes, taking account of the matrix of excess return correlations or of their relative contributions to tracking error risks, would have led to much better results in terms of relative risks: that is the objective of the relative risk management of smart beta allocations.

Moreover, by using the diversified multi-strategy weighting scheme, these indexes provide simple diversification of unrewarded risks but do not explicitly account for the correlation across different weighting strategies, which, for the same factor tilt, can be considerably below 1 and therefore corresponds to a potential improvement in risk-adjusted performance when it is taken into account. Exhibit 3 illustrates this point and shows that it is possible to be able to benefit from an attractive average pairwise correlation that justifies the use of different indexes corresponding to different diversification strategies for the same factor tilt. Naturally, approaches that take account of extreme correlations will be able to benefit from maximizing the diversification between these smart factor indexes.

Exhibit 4 provides performance and risk results for a simple multi-beta multi-strategy combination. This involves combining the smart factor indices represented by Diversified Multi-Strategy US Value, Low Volatility, Momentum and Mid-Cap in equal quantities. The performance and risk of the combination of these four factor-tilted multi-strategy indexes is compared to the stand-alone performance and risk of each multi-strategy factor-tilted index.

It is of particular interest to compare the risk-adjusted relative performance (information ratio) of the combination to the stand-alone results obtained by each single factor tilt. While the single factor-tilted indexes all generate positive information ratios, the results display considerable differences across factor tilts with an information ratio (IR) of 0.48 for the low-volatility index to an IR of 0.82 for the value index. Interestingly, the multi-beta multi-strategy equal weight index obtains an IR which is almost identical to the best result obtained among all the single factor tilts. The IR of the multi-factor combination is indeed higher than the average information ratio of the four factor-tilted indexes which make up its components. In fact, the IR of the Scientific Beta Multi-Beta Multi-Strategy EW index of 0.79 compared to the average IR of the component indexes of 0.69 corresponds to a 14.5% increase in IR. This clearly shows the allocation effect of diversifying across different factor tilts, which elevates risk-adjusted performance relative to the average result for component indexes. In a nutshell, the results in Exhibit 4 provide evidence that choosing good factor tilts generates attractive risk-adjusted performance, and that combining them allows the relative risk-adjusted return to be improved.

Tailored risk allocation with smart factor indexes

The standard multi-beta multi-strategy indexes provide simple access to the combination benefits of several smart beta strategies. The standard indexes provide equal allocations both to the weighting schemes, and to the factor tilts. They thus provide a first attempt at diversifying away weighting-scheme-specific risk, as well as allocating across multiple sources of rewarded risk (factor tilts). However, it is entirely possible to conceive of improved allocation schemes which account for the risk properties of the different weighting schemes and factor tilts. Such risk allocation approaches can provide less naive ways of allocating based on specific objectives.

In an attempt to identify, and analyze the benefits of, the possible approaches to efficient risk allocation across the various smart factor indexes, we identify four main dimensions that can be taken into consideration when designing a sophisticated allocation methodology (see Exhibit 5).

The first, and arguably most important, dimension relates to whether risk is defined by the investor from an absolute perspective in the absence of a benchmark, or whether it is instead defined in relative terms with respect to an existing benchmark, which is more often than not a cap-weighted index. In the former situation, one would use volatility as a relevant risk measure, while tracking error with respect to the cap-weighted index would instead be used in the latter case.

In the case of absolute risk allocation, a commonly important case is to define a benchmark with the best risk-adjusted return characteristics. This improvement will come for example from the reduction in benchmark risk through a

EXHIBIT 2

Correlation of excess returns across factor tilts.
All statistics are annualized and daily total returns from 12/31/1974 to 12/31/2014 are used for the US long-term universe. The universe contains 500 stocks. The full names of the indexes used are: SciBeta United States LTTR Mid-Cap Diversified Multi-Strategy, SciBeta United States LTTR High-Momentum Diversified Multi-Strategy, SciBeta United States LTTR Low-Volatility Diversified Multi-Strategy, SciBeta United States LTTR Value Diversified Multi-Strategy, SciBeta United States LTTR Low Investment Diversified Multi-Strategy and SciBeta United States LTTR High Profitability Diversified Multi-Strategy. Source: www.scientificbeta.com.

SciBeta US Long-Term Track Records (Dec 1974 - Dec 2014)		Diversified Multi-Strategy				
		Momentum	Low Volatility	Value	Low Investment	High Profitability
Diversified Multi-Strategy	Mid Cap	0.67	0.63	0.86	0.85	0.74
	Momentum		0.61	0.64	0.74	0.65
	Low Volatility			0.7	0.82	0.60
	Value				0.84	0.51
	Low Investment					0.69

EXHIBIT 3

Average pairwise correlations of excess returns across five weighting schemes.
The analysis is based on daily total returns of US Long-Term Track Records from 12/31/1974 to 12/31/2014. The average, minimum and maximum pairwise correlations across the five weighting schemes – Max Deconcentration, Max Decorrelation, Max Sharpe Ratio, Min Volatility and Diversified Risk Weighted for the six factors – Momentum, Low Volatility, Value, Size, Low Investment and Low Profitability are provided. Source: www.scientificbeta.com

SciBeta US Long-Term Track Records						
(Dec 1974 - Dec 2014)	Momentum	Low Volatility	Value	Size	Low Investment	High Profitability
Average correlation across five weighting schemes	0.87	0.96	0.87	0.89	0.89	0.85
Maximum correlation across five weighting schemes	0.96	0.99	0.97	0.97	0.97	0.96
Minimum correlation across five weighting schemes	0.71	0.91	0.73	0.74	0.77	0.64

EXHIBIT 4

Performance benefits of USA multi-beta multi-strategy indexes.
The table compares the performance and risk of the Scientific Beta Diversified Multi-Strategy US Long-Term Track Records. The Scientific Beta Multi-Beta Multi-Strategy EW index is the equal-weighted combination of the four Diversified Multi-Strategy indexes with stock selection based on Mid Cap, Momentum, Low Volatility, and Value respectively. All statistics are annualized and daily total returns from 12/31/1974 to 12/31/2014 are used for the analysis. The SciBeta CW US-500 index is used as the cap-weighted benchmark. The yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. The full names of the US indexes used are: SciBeta United States Mid-Cap Diversified Multi-Strategy, SciBeta United States High-Momentum Diversified Multi-Strategy, SciBeta United States Low-Volatility Diversified Multi-Strategy, SciBeta United States Value Diversified Multi-Strategy, SciBeta United States Multi-Beta Multi-Strategy EW and SciBeta United States Multi-Beta Multi-Strategy ERC. Source: www.scientificbeta.com.

SciBeta US Long- Term (Dec 1974 - Dec 2014)	Diversified Multi-Strategy						
	SciBeta US Broad CW	Mid Cap	Momentum	Low Vol.	Value	Average across four tilts	Multi-Beta Multi-Strategy EW
Ann. Returns	12.16%	16.75%	15.65%	15.03%	16.70%	16.03%	16.11%
Ann. Volatility	17.12%	16.57%	16.12%	14.16%	16.37%	15.81%	15.58%
Sharpe Ratio	0.41	0.70	0.65	0.70	0.71	0.69	0.71
Max. Drawdown	54.53%	58.11%	49.00%	50.13%	58.41%	53.91%	53.86%
Excess Returns	-	4.59%	3.49%	2.87%	4.54%	3.87%	3.95%
Tracking Error	-	6.38%	4.72%	6.04%	5.56%	5.68%	4.98%
95% Tracking Error	-	11.42%	8.58%	11.53%	10.14%	10.42%	8.95%
Information Ratio	-	0.72	0.74	0.48	0.82	0.69	0.79
Outperf. Prob. (3Y)	-	74.38%	83.13%	76.04%	78.73%	78.07%	80.38%

minimum volatility allocation or with the constraint of a volatility budget relative to that of the cap-weighted index to benefit from the asymmetry of volatility in bull and bear markets. It is this case that we will present in our low risk benchmark construction exercises.

The relative risk approach can give rise to the application of numerous techniques. EDHEC Risk Institute has carried out cases of equalizing the contribution to tracking error risk and even creating multi-factor portfolios under the constraint of a market beta equal to that of the reference cap-weighted index to minimize the extreme tracking error risk relating for example to an overly defensive exposure of the smart beta portfolio, as is often the case. This approach, which we present in a contribution to this supplement, enables the tracking error risk to be limited while preserving the smart beta portfolio's strong exposure to the risks that are rewarded over the long term. In addition, good diversification of the idiosyncratic relative risk will ultimately optimize the relative risk-adjusted return, which will only depend on a deliberate choice of well-rewarded factors.

Relative risk objectives may also be defined in an asset-liability-management framework, rather than an asset-management-only framework. Moreover, it is feasible, and may more often than not be potentially desirable, to improve the relevance of portfolios and the resulting investment outcomes by designing highly-customized efficient multi-factor equity portfolio solutions that are optimized from an asset-liability management perspective that reflects the investor's specific investment context. For example, a mature pension fund facing a stream of bond-like pension obligations may find it useful to select stocks that show an above-average degree of "liability-friendliness," which can be measured for example in terms of their correlation or tracking error with respect to a liability proxy and/or their ability to pay a high and predictable stream of dividends. Once these stocks are selected, a dedicated efficient factor index can be designed, and used as an additional building block in allocation exercises dedicated to achieving the optimal trade-off between liability-hedging benefits and performance benefits. This approach, which was presented by EDHEC Risk Institute as part of research conducted by Coqueret, Deguest, Martellini, and Milhau (2014)[9] allows investment in a portfolio that not only has a good Sharpe ratio but also better correlation with the liabilities, which, for a given level of funding ratio volatility, enables the investment in the performance-seeking portfolio to be increased.

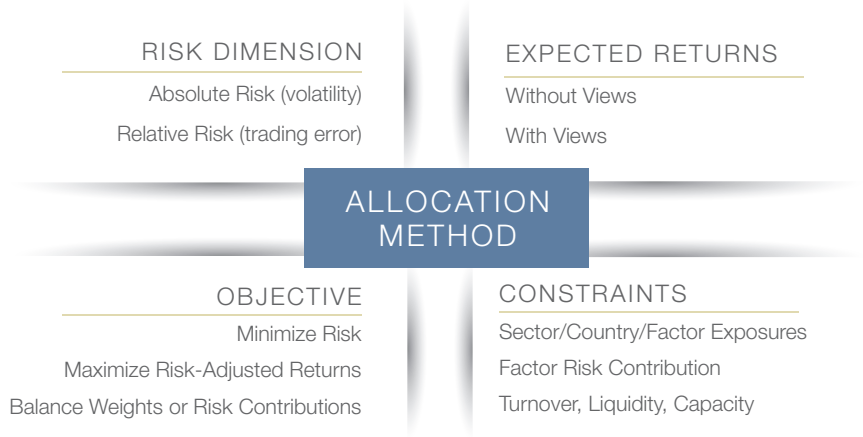
The second dimension concerns whether one would like to incorporate views regarding factor returns in the optimization process. While additional benefits can be obtained from the introduction of views on factor returns at various points of the business cycle, we focus in what follows only on approaches that are solely based on risk parameters, which are notoriously easier to estimate with a sufficient degree of robustness and accuracy (Merton (1980)).

The third dimension is related to the objective of the allocation procedure. There are several possible targets for the design of a well-diversified portfolio of factor exposure, depending upon whether one would like to use naive approaches (equal dollar allocation or equal risk allocation) or scientific approaches based on minimizing portfolio risk (volatility in the absolute return context or tracking error in the relative return context). The fourth and last dimension related to the presence of various forms of constraints such as minimum/maximum weight constraints, turnover constraints, or factor exposure constraints, which are obviously highly relevant in the context of risk factor allocation.

In practice, investors may thus select among various ways of combining smart factor indexes in order to account for their investment beliefs, objectives and constraints. The following two articles in this supplement provide illustrations where multi-smart-beta allocations are crafted in order to accommodate investors' particular objectives and investment context. While possibilities for adding value through smart beta allocation are manifold, the robust performance improvements obtained through simple equal-weighted allocations to the five weighting schemes and the main consensual factors displayed above in this article, provide evidence that the benefits of multi-factor allocations are sizable. Investors and asset managers may be well- advised to further explore the potential of multi-factor allocations in a variety of investment contexts. •

EXHIBIT 5

The various dimensions of allocation methodologies across assets or risk factors



The following two articles in this supplement provide illustrations where multi-smart-beta allocations are crafted in order to accommodate investors' particular objectives and investment context.

References

Coqueret G., R. Deguest, L. Martellini and V. Milhau, *December 2014, Equity Portfolios with Improved Liability-Hedging Benefits, EDHEC Risk Institute working paper.*

Merton, R. *1980. On Estimating the Expected Return on the Market: An Exploratory Investigation. Journal of Financial Economics 8 (4): 323–361.*

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INDEXES

Absolute Risk Allocation with Smart Factor Indexes

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Traditional approaches to defensive smart beta strategies

There are two popular ways to implement defensive smart beta strategies – one based on minimum variance portfolios and another relying on the selection of low-volatility stocks.

The first approach refers to the traditional mean-variance framework from Modern Portfolio Theory. The Global Minimum Variance (GMV) portfolio is a portfolio on the efficient frontier in the sense that there is no portfolio that has a better return for the same level of risk. It is not the optimal portfolio (i.e. the maximum Sharpe ratio) but the advantage is that it is not necessary to estimate expected returns in order to construct the portfolio. This parsimonious parameter estimation is actually a popular construction technique among managers and investors. The defensive nature of the portfolio, since it is the efficient portfolio with the lowest level of risk, has allowed these portfolios to exhibit very good performance relative to cap-weighted indexes in highly volatile markets and their track record has benefited from the recent crises of 2008 and 2011.

The second approach is a two-step process where one selects stocks that exhibit low volatility and then weights them either using a well-diversified weighting scheme, or cap-weighting, or an ad-hoc weighting scheme such as score-weighted. The low-volatility selection has received considerable interest, notably since the work of Ang et al., (2006), who showed that low-volatility stocks did not necessarily produce lower returns than high-volatility stocks, and indeed produced higher returns. Haugen and Heins (1972, 1975) analyze pitfalls in commonly-used cross-sectional tests of the risk-return relationship, and express doubts regarding the existence and significance of the risk premia implied by standard asset pricing models. Blitz and Van Vliet (2007) show that portfolios of low-volatility stocks have higher returns than portfolios of high-volatility stocks because investors overpay for volatility, possibly because of leverage restrictions. Similarly, Baker, Bradley, and Wurgler (2011) find that portfolios formed by sorting stocks by past volatility display higher returns for the low-volatility quintile over the subsequent month than for the high-volatility quintile. Baker, Bradley and Wurgler (2011) explain the low-volatility premium by the lottery preferences of investors and Hong and Sraer (2012) show that in the presence of short-sale constraints, the disagreement among investors on the future cash flow of firms leads to overpricing of stocks. As disagreement increases with a stock's beta, high-beta stocks are more likely to be overpriced.

More recently, it has been shown that there was a low-volatility risk premium that can be explained by economic reasoning. For example, Frazzini and Pedersen (2014) argue that liquidity-constrained investors are able to invest in leveraged positions of low-beta assets but are forced to liquidate these assets in bad times when their liquidity constraints mean they can no longer sustain the leverage, thus exposing themselves to the risk of liquidity shocks. This rational explanation means that low-volatility stocks are considered to be representative of a risk factor that is rewarded over the long term.

The objective of the Scientific Beta Efficient Minimum Volatility strategy is to minimize the overall portfolio volatility by using the information on pair-wise correlations and volatilities of stocks. The aim is thus to provide a good proxy for the least risky portfolio in the MPT framework.[10] In order to avoid the problem of concentration in low-volatility stocks in the resulting portfolio, flexible de-concentration constraints are also imposed.[11] Post-optimization, the long-only adjustment follows:

$$(1)\quad w^* = \arg\min \left\{ \sqrt{w^T * \Sigma * w} \right\} \qquad \sum_{i=1}^{N} w_i = 1 \qquad \frac{1}{w^T * w} \geq \frac{N}{3}$$

With regard to the second approach of making an explicit or implicit choice of exposure to the low-volatility factor, Scientific Beta Low Volatility Multi-Strategy addresses this problem by constructing a smart factor index on the low-volatility factor. The Low Volatility Multi-Strategy portfolio is constructed using the Smart Beta 2.0 approach, a two-step process (Amenc et al. (2013)). The idea is to construct a factor-tilted portfolio to extract the low-volatility factor premia most efficiently and is based on two pillars: 1) explicitly selecting low-volatility stocks – the stocks with the lowest past-two-year volatility and 2) using a diversification-based weighting scheme known as Diversified Multi-Strategy.

Stock-specific risk can be reduced through the use of a suitable diversification strategy such as maximum Sharpe ratio or minimum volatility. However, due to imperfections in the diversification model used, residual exposures to unrewarded strategy-specific risks remain. Furthermore, in spite of all the attention paid to the quality of model selection and the implementation methods for these models, the specific operational risk remains present to some extent. The Diversified Multi-Strategy approach, which combines the five different weighting schemes in equal proportion,[12] is based on this specific risk diversification principle (Kan and Zhou (2007)) and it enables the non-rewarded risks associated with each of the weighting schemes to be diversified away.

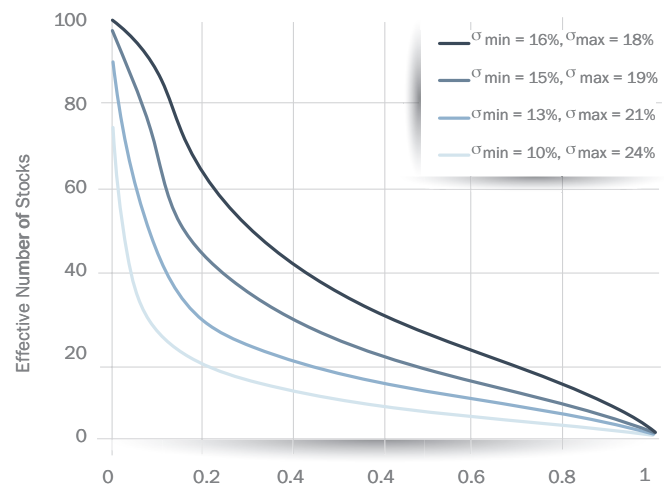
The similarity between these two approaches is that both lead to the overweighting of low-volatility stocks. While the Low Volatility Multi-Strategy approach does it explicitly by discarding the 50% of stocks with the highest volatility, the Efficient Minimum Volatility strategy does it implicitly. Although the minimum-volatility optimizer takes into account both the volatility and correlations of stocks, it is a well-documented fact that the minimum-volatility optimizer overweights stocks that have low volatility. In other words, when the objective is minimization of total portfolio volatility, the volatility characteristic of a stock plays a more important role than its correlation with other stocks. Exhibit 1 shows that the more diverse the volatilities in the universe are, the more concentrated the GMV is in the lower volatility assets. Despite having extremely low correlations, the problem of high concentration occurs when the dispersion in volatility across stocks is high.

In both cases, the resulting portfolios concentrate on low-volatility stocks. Therefore, the choice of constraints that tackle the problem of high concentration plays an important role in determining the performance and risk of minimum-volatility portfolios. The high concentration problem of minimum-volatility strategies has been long documented (Chan et al. (1999), Clarke et al. (2011), DeMiguel et al. (2009)) and consequently there exists a large body of academic research that aims at dealing with this specific problem.

The most straightforward way to avoid this problem is by using rigid constraints on stock weights, sector weights, or country weights (in the case of multi-country regions). For example, the MSCI USA Minimum Volatility index uses rigid constraints in their optimizer. Individual stocks are subject to a fixed lower bound and an upper bound determined by their market capitalization. The sector weights are also bounded between levels determined by parent index sector weights.[13]

EXHIBIT 1

Role of Stock Volatilities and Stock Correlation in GMV optimization.
The figure is obtained from Amenc et al. (2011) (an ERI research paper entitled "A Post-Crisis Perspective on Diversification for Risk Management"). The authors consider a hypothetical universe of 100 stocks, the annualized volatilities of which are equally spaced in the following ranges: [16%, 18%], [15%, 19%], [13%, 21%], and [10%, 24%]. In the three cases, the average volatility is one and the same; the only difference is the dispersion of the volatilities around the average. On these assumptions, they numerically calculate the GMV portfolios for degrees of correlation ranging from 0 to 0.99 in a constant correlation model.



[10] For a complete description of how the strategy is implemented we refer the reader to the Strategy Construction Rules of the Scientific Beta Efficient Minimum Volatility Indices available at www.scientificbeta.com.
[11] These flexible de-concentration or "norm" constraints are discussed in more detail in the upcoming sections of this article.
[12] Diversified Multi-Strategy weighting is an equal-weighted combination of the following five weighting schemes - Maximum Deconcentration, Diversified Risk Weighted, Maximum Decorrelation, Efficient Minimum Volatility and Efficient Maximum Sharpe Ratio.
[13] The weight constraints can be relaxed to handle infeasible optimizations. Other constraints relating to risk factor exposure and turnover are also used. The methodological details are obtained from the following web link: https://www.msci.com/resources/pdfs/MSCI_Minimum_Volatility_Indexes_Investor_Insight.pdf.

This approach is very popular due to its simple nature but it has two drawbacks. First, there is a potential for "ex-post optimization" of such ad-hoc constraints, meaning that the constrained portfolio is sub-optimal by definition. The second problem is that these kinds of constraints do not allow the risk reduction potential of the covariance structure of returns to be fully utilized.

DeMiguel et al. (2009) go beyond considering rigid constraints at the individual stock level and introduce flexible constraints on overall portfolio concentration (so-called "norm constraints"). They show that such flexible concentration constraints, instead of rigid upper and lower bounds on individual stock weights, allows for better use of the correlation structure and therefore leads to better out-of-sample risk and return properties for minimum-volatility portfolios. The results in Exhibit 2 show that the norm-constrained portfolio makes more efficient use of the risk budget compared to the rigidly-constrained portfolio. The Sharpe ratio of the Scientific Beta USA Efficient Minimum Volatility strategy is superior to that of MSCI USA Minimum Volatility.

Benefits of factor diversification and weighting schemes

Although norm constraints prove to be an excellent way to de-concentrate at the stock level, they do not guarantee diversification of risks at the risk-factor or weighting-scheme level. The norm constraint approach is applied at the stock level and not at the risk-factor level. It will therefore be possible to have a portfolio that is not very concentrated but remains highly concentrated at the factor level i.e. that is globally a portfolio that is exposed to stocks with lower volatility than the average in the universe. In this sense, the exposure to low-volatility risk is not very different between the Scientific Beta Low-Volatility Multi-Strategy indexes and the Scientific Beta Efficient Minimum Volatility indexes.

In view of this observation, it seems reasonable to envisage constructing benchmarks that take account of the limitations of the abovementioned approaches in terms of factor diversification. That is the sense of the approach designed by EDHEC Risk within the framework of smart allocation between smart beta indexes, which provides factor-diversification and weighting-scheme-diversification benefits. This smart allocation is based on the idea of conducting risk allocation that relies on indexes that are representative of differentiated exposure to both risk factors and weighting schemes. The ingredients in this allocation (i.e. the indexes used) are the same as those that are contained in Scientific Beta's Multi-Beta Multi-Strategy offering.

For the implementation of this smart allocation, 30 factor indexes representing a choice of six systematic risk factors associated with five weighting schemes are used. The six factors are Mid-Cap, Value, Momentum, Low Volatility, Low Investment and High Profitability.[14] The five weighting schemes are Maximum Deconcentration, Diversified Risk Weighted, Maximum Decorrelation, Efficient Minimum Volatility and Efficient Maximum Sharpe Ratio. The GMV allocation under 1/3 norm constraints is performed on these ingredients.

The allocation problem can be written mathematically as:

$$w^* = \underset{\substack{\sum_{i=1}^{N} w_i = 1 \\ w_i \geq 0 \forall_i \\ \frac{1}{w^T * w} \geq \frac{N}{3}}}{argmin} \left\{ \sqrt{w^T * \Sigma * w} \right\} \quad (2)$$

W_i represents the weight of the i-th constituent. N is the number of constituents. Σ is the covariance matrix of total returns. Weekly total returns over the past 104 weeks are used to estimate the covariance matrix.

Exhibit 3 shows the fractional weights of the 30 smart factor indexes in the GMV allocation. It is interesting to see that, unlike what is observed with traditional GMV or low-volatility indexes, smart allocation with different factor indexes allows the benchmark's exposure to risk factors to be genuinely diversified. Exhibit 3 clearly shows significant exposure over time to factors other than the low-volatility factor; which means that the factor risk is well diversified.

The results of this GMV allocation with 30 factor indexes are consistent with this good level of risk diversification. Exhibit 4 shows that the norm-constrained GMV allocation across smart factor indexes fulfils the objective of overall volatility reduction. It achieves lower volatility then the first two approaches – Efficient Minimum Volatility and Low Volatility Multi-Strategy. Its performance remains high in comparison to these two approaches because it benefits from explicit exposure to the six long-term rewarded factors. In this sense, it is similar to the performance of a Multi-Beta Multi-Strategy benchmark that would contain, in equal proportions, exposure to six well-diversified multi-strategy factor indexes representative of the Value, Mid-Cap, Momentum, High Profitability, Low Investment and Low Volatility factors, while having lower volatility and therefore a smaller maximum drawdown. Due to diversification of risk factors, the maximum relative drawdown also falls to 48.36%, compared to 54.53% for that of the benchmark.

The drawback of this approach is that its relative performance is highly dependent on market conditions. In particular, the strategy outperforms by large margins in bear markets but its outperformance in bullish markets is quite poor, notably in periods of extreme bull markets. This problem is common to the other two defensive strategies as well. This kind of allocation is attractive for an investor who wants to protect the portfolio value (or reduce the losses) in bear markets. Therefore, it is complementary to most actively-managed portfolios, which are known to have high market beta.

Dissymmetric defensive smart allocation

To respond to the problem posed by the underperformance of defensive strategies in the event of bull markets, EDHEC Risk has designed a smart allocation methodology that is no longer based on the absolute risk allocation objective that corresponds to an absolute reduction (and therefore a constant reduction in volatility budget), but instead to a relative reduction in the volatility budget. In this case, it involves reducing the volatility of the defensive benchmark in proportion to the observed volatility of the cap-weighted index. This reduction in volatility therefore varies depending on the volatility of the cap-weighted index.

EXHIBIT 2

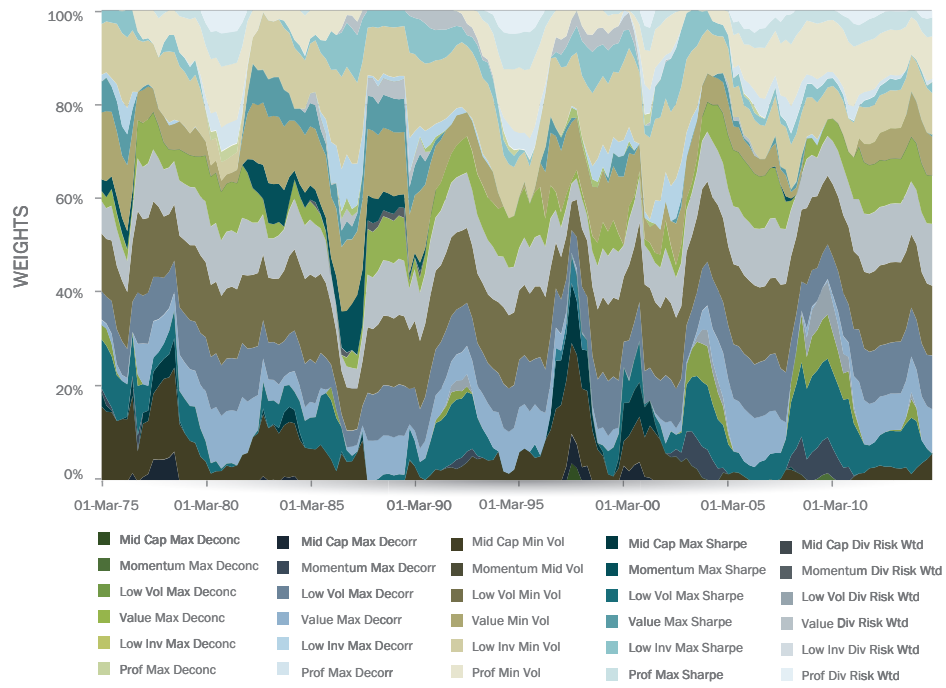
Flexible Norm Constraints and Rigid Constraint Minimum Volatility Portfolios.
The analysis is based on daily total returns in USD in the period 31-Dec-2004 to 31-Dec-2014 (10 years). All statistics are annualized. Yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. Maximum relative drawdown is the maximum drawdown of the long-short index whose return is given by the fractional change in the ratio of the strategy index to the benchmark index. Probability of outperformance is the probability of obtaining positive excess returns if one invests in the strategy for a period of 1 (or 3 or 5) years at any point during the history of the strategy. Rolling window of length 1 (or 3 or 5) years and a step size of 1 week is used. The corresponding average relative returns is the average of relative returns across all rolling windows and the corresponding average of positive relative returns is the average across rolling windows where the relative returns are positive. The Scientific Beta USA universe contains 500 stocks. Source: scientificbeta.com and Bloomberg.

31-Dec-2004 to 31-Dec-2014 (10 Years)	Scientific Beta USA CW	Scientific Beta USA Efficient Min Volatility	MSCI USA Minimum Volatility
Ann. Returns	7.90%	10.34%	8.96%
Ann. Volatility	20.26%	17.51%	16.91%
Sharpe Ratio	0.32	0.51	0.45
Maximum Drawdown	54.63%	47.33%	46.61%
Ann. Rel. Returns	-	2.44%	1.06%
Tracking Error	-	4.14%	5.20%
Information Ratio	-	0.59	0.20
Outperf. Prob. (1Y)	-	66.60%	44.26%
Average Rel. Returns	-	1.66%	0.03%
Average of Positive Rel. Ret	-	3.46%	5.12%
Outperf. Prob. (3Y)	-	93.44%	80.05%
Average Rel. Returns	-	2.32%	1.61%
Average of Positive Rel. Ret.	-	2.52%	2.39%
Outperf. Prob. (5Y)	-	100.00%	79.39%
Max Relative Drawdown	-	7.51%	13.26%

EXHIBIT 3

Constrained GMV Allocation Weights.
The figure shows the evolution of weights across the 30 smart factor indexes.

Global Minimum Volatility (1/3 Norm): Weights



[14] *The following selection rules are applied to select stocks for each tilt: Mid-Cap: bottom 50% free-float-adjusted market-cap stocks are selected. Value: top 50% stocks are selected by book-to-market (B/M) ratio. B/M is defined as the ratio of available book value of shareholders' equity to company market cap; High Momentum: top 50% stocks are selected by returns over past 52 weeks, minus the last 4 weeks; Low Volatility: bottom 50% stocks are selected by their standard deviation of weekly stock returns over the past 104 weeks; High Profitability: top 50% stocks with highest Gross Profit/Total Asset ratio are selected; Low Investment: bottom 50% stocks with least 2-Year total asset growth rate are selected. This score-based selection is done twice a year (June and December) for Momentum and once a year (June) for the other three factors.*

This approach enables us to perform dissymmetric defensive allocations. This risk allocation method allows the level of defensive nature to be adjusted based on the state of market using the asymmetrical property of market volatility in bull and bear markets. In general, low-volatility markets are correlated with bull markets, which are not a favorable regime for defensive portfolios.

We perform a maximum deconcentration allocation with a constraint of 90% of market volatility. This approach aims to create asymmetry by reducing the defensive character of the portfolio when the cap-weighted volatility is decreasing. The allocation problem can be written mathematically as:

(3)

$$w^* = ar\,gmax\{1/(w^T * w)\} \begin{cases} \sum_{i=1}^{N} w_i = 1 \\ w_i \geq 0 \forall_i \\ \sqrt{w^T * \Sigma * w} \leq 90\% * Volatility_{CW} \end{cases}$$

W_i represents the weight of the i-th constituent. N is the number of constituents. $\sum$ is the covariance matrix of total returns. Weekly total returns over the past 104 weeks are used to estimate the covariance matrix and benchmark volatility.

Exhibit 6 shows that the volatility-constrained maximum deconcentration allocation achieves low levels of volatility (14.66%) compared to that of a broad CW index (17.12%) and a simple equal-weighted allocation – the Multi-Beta Multi-Strategy 6-Factor EW (15.52%). Due to well-diversified exposure to the six rewarded factors, it shows strong outperformance of 3.68%. Since this allocation is not "defensive" at all times, its overall tracking error is also improved compared to the other three defensive approaches. As a result, it delivers a high information ratio of 0.73 over a 40-year period.

More importantly, its conditional performance is more symmetrical. While the norm-constrained GMV's outperformance is -3.94% and 7.79% in extreme bull and extreme bear markets respectively, the volatility-constrained maximum deconcentration allocation's conditional performances are 0.34% and 5.95% respectively. Even though most of the performance of this dissymmetric allocation comes from bear markets, we observe that even in extreme bull markets the investor has similar performance to the cap-weighted index.

CONCLUSION: effectiveness of smart allocation solutions

The profusion of smart beta indexes, which is often stimulated by new index construction ideas, leads to a risk of model mining or factor fishing. Many index providers multiply innovations in order to distract from the poor out-of-sample performance of methodologies that were designed to perform in-sample, notably because they were well exposed to a factor that was highly rewarded over the period that corresponded to the simulated track record (Amenc et al. (2015)).

The success of GMV with many smart beta investors is explained by the confusion maintained with the low-volatility anomaly, which does not necessarily lead to the adoption of a minimum-volatility index, with the minimum-volatility performance observed during the recent financial crises, but rather to a low-volatility index,.

The objective of this article is not therefore to propose a new index that is constructed to optimize performance over a recent period, but to show that on the basis of existing smart factor indexes, allocation between these indexes can allow an investor who wishes to implement a defensive strategy to avoid concentration in a single factor and above all to benefit from the particular properties of volatility and its dissymmetric nature with respect to market conditions, and thereby adjust the portfolio's defensive bias to market conditions.

Exhibit 7 shows that smart allocation solutions on a set of smart factor indexes always give a better result than the traditional minimum-volatility approaches, which are either mono-factor dependent or else, due to rigid constraints defined in-sample, give disappointing out-of-sample results. Specifically, we observe that a norm-constraint GMV weighting applied to a set of indexes representative of factors that are well rewarded over the long term gives much better risk-adjusted performance and above all, much better conditional performance, when comparing for example MSCI Minimum Volatility and Maximum Deconcentration with an ex-ante relative volatility constraint of 90%. Naturally, these better conditional performances procure much better information ratios and, above all, much better outperformance probabilities. •

EXHIBIT 4

Norm-Constrained GMV Allocation across Smart Factor Indexes compared to Traditional Approaches.
statistics are annualized. Yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. Reported turnover is one-way annual and it is averaged across 160 rebalancings in the 40-year period. All allocations are systematically rebalanced quarterly. Maximum relative drawdown is the maximum drawdown of the long-short index whose return is given by the fractional change in the ratio of the strategy index to the benchmark index. Probability of outperformance is the probability of obtaining positive excess returns if one invests in the strategy for a period of 1 (or 3 or 5) years at any point during the history of the strategy. Rolling window of length 1 (or 3 or 5) years and a step size of 1 week is used. Corresponding average relative returns is the average of relative returns across all rolling windows and corresponding average of positive relative returns is the average across rolling windows where the relative returns are positive. Quarters with positive benchmark index returns are bull quarters and the remaining are bear quarters. Top 25% quarters with best benchmark index returns are extreme bull quarters and bottom 25% quarters with worst benchmark index returns are extreme bear quarters. The Scientific Beta USA LTTR universe contains 500 stocks. The Multi-Beta Multi-Strategy is based on 30 underlying strategies which are combinations of six factor tilts (mid-cap, value, high momentum, low volatility, high profitability and low investment) and five diversification-based weighting schemes (Max. Deconcentration, Max Decorrelation, Eff. Min Volatility, Eff. Max Sharpe and Div. Risk Weighted). The GMV allocation under 1/3 Norm Constraint is also based on these 30 underlying strategies. Source: scientificbeta.com/Scientific Beta USA Long-Term Track Records.

31-Dec-1974 to 31-Dec-2014 (40 Years)	Broad CW Index	GMV Allocation (Norm 1/3)	Multi-Beta Multi-Strategy 6-Factor (EW)	Scientific Beta USA LTTR Efficient Min Volatility	Scientific Beta USA LTTR Low Volatility Multi-Strategy
Ann. Returns	12.16%	15.51%	16.01%	14.65%	15.03%
Ann. Volatility	17.12%	14.14%	15.52%	14.50%	14.16%
Sharpe Ratio	0.41	0.74	0.70	0.66	0.70
Maximum Drawdown	54.53%	48.36%	52.83%	50.03%	50.13%
Ann Rel. Returns	-	3.35%	3.86%	2.50%	2.87%
Tracking Error	-	5.78%	4.73%	5.09%	6.04%
Information Ratio	-	0.58	0.81	0.49	0.48
Outperf. Prob. (1Y)	-	70.19%	74.61%	71.66%	66.06%
Avg. Rel. Returns	-	2.96%	3.61%	2.19%	2.52%
Avg. of Positive Rel. Ret.	-	6.55%	6.50%	5.16%	6.30%
Outperf. Prob. (3Y)	-	80.23%	81.16%	79.35%	76.04%
Avg. Rel. Returns	-	3.00%	3.48%	2.22%	2.64%
Avg. of Positive Rel. Ret	-	5.07%	5.29%	4.12%	4.69%
Outperf. Prob. (5Y)	-	86.98%	89.99%	80.42%	85.39%
Max. Relative Drawdown	-	41.49%	32.88%	40.10%	43.46%
Rel. Ret. Bull Markets	-	0.25%	2.98%	-0.07%	-0.85%
Rel. Ret. Bear Markets	-	7.82%	4.86%	6.16%	8.35%
Rel. Ret. 25% Bull Markets	-	-3.94%	3.42%	-3.84%	-5.90%
Rel. Ret. 25% Bear Markets	-	7.79%	4.59%	6.02%	8.50%
1-Way Ann. Turnover	2.7%	34.2%	25.0%	30.3%	25.8%

EXHIBIT 5

Volatility-Constrained Maximum Deconcentration Allocation Weights.
The figure shows the evolution of weights across the 30 smart factor indexes.

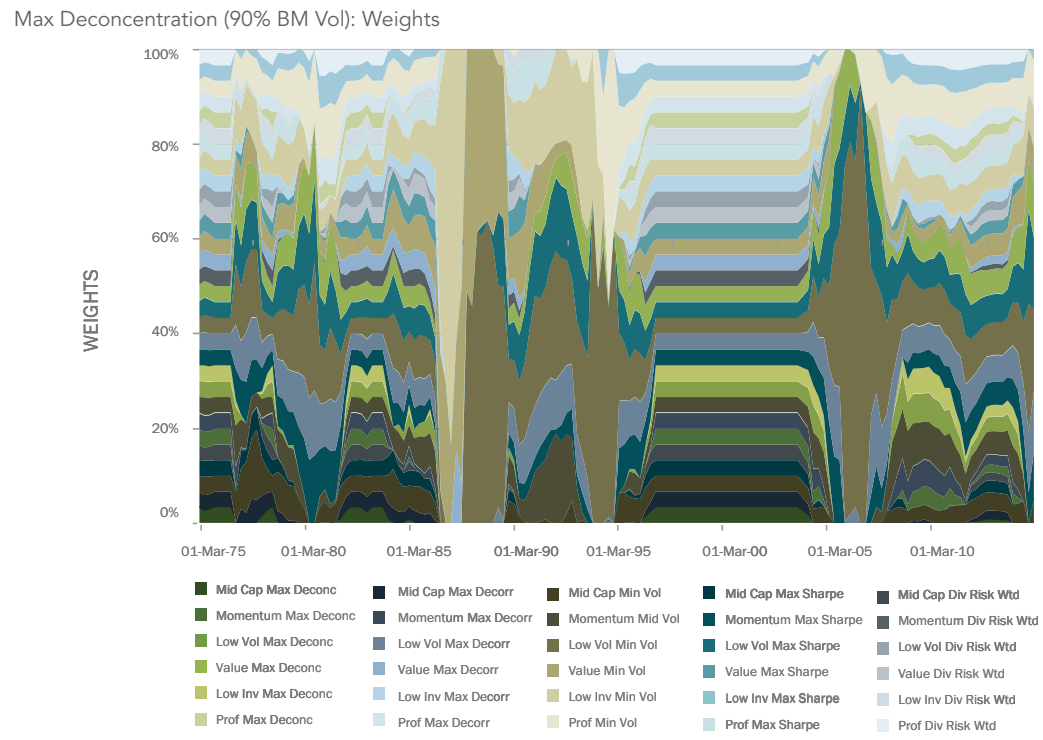


EXHIBIT 6

Volatility-Constrained Maximum Deconcentration Allocation Compared to Defensive Approaches.
The analysis is based on daily total returns in USD in the period 31-Dec-1974 to 31-Dec-2014 (40 years). All statistics are annualized. Yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. Reported turnover is one-way annual and it is averaged across 160 rebalancings in the 40-year period. All allocations are systematically rebalanced quarterly. Maximum relative drawdown is the maximum drawdown of the long-short index whose return is given by the fractional change in the ratio of the strategy index to the benchmark index. Probability of outperformance is the probability of obtaining positive excess returns if one invests in the strategy for a period of 1 (or 3 or 5) years at any point during the history of the strategy. Rolling window of length 1 (or 3 or 5) years and a step size of 1 week is used. Corresponding average relative returns is the average of relative returns across all rolling windows and corresponding average of positive relative returns is the average across rolling windows where the relative returns are positive. Quarters with positive benchmark index returns are bull quarters and the remaining are bear quarters. Top 25% quarters with best benchmark index returns are extreme bull quarters and bottom 25% quarters with worst benchmark index returns are extreme bear quarters. The Scientific Beta USA LTTR universe contains 500 stocks. The Multi-Beta Multi-Strategy is based on 30 underlying strategies which are combinations of six factor tilts (mid-cap, value, high momentum, low volatility, high profitability and low investment) and five diversification-based weighting schemes (Max. Deconcentration, Max Decorrelation, Eff. Min Volatility, Eff. Max Sharpe and Div. Risk Weighted). The GMV allocation under 1/3 Norm Constraint is also based on these 30 underlying strategies. Source: scientificbeta.com/Scientific Beta USA Long-Term Track Records.

31-Dec-1974 to 31-Dec-2014 (40 Years)	Broad CW Index	GMV Allocation (Norm 1/3)	Max Deconcentration (90% BM Vol)	Multi-Beta Multi-Strategy 6-Factor (EW)	Scientific Beta USA LTTR Efficient Min Volatility	Scientific Beta USA LTTR Low Volatility Multi-Strategy
Ann. Returns	12.16%	15.51%	15.84%	16.01%	14.65%	15.03%
Ann. Volatility	17.12%	14.14%	14.66%	15.52%	14.50%	14.16%
Sharpe Ratio	0.41	0.74	0.73	0.70	0.66	0.70
Maximum Drawdown	54.53%	48.36%	48.99%	52.83%	50.03%	50.13%
Ann Rel. Returns	-	3.35%	3.68%	3.86%	2.50%	2.87%
Tracking Error	-	5.78%	5.01%	4.73%	5.09%	6.04%
Information Ratio	-	0.58	0.73	0.81	0.49	0.48
Outperf. Prob. (1Y)	-	70.19%	70.97%	74.61%	71.66%	66.06%
Avg. Rel. Returns	-	2.96%	3.28%	3.61%	2.19%	2.52%
Avg. of Positive Rel. Ret.	-	6.55%	6.40%	6.50%	5.16%	6.30%
Outperf. Prob. (3Y)	-	80.23%	80.18%	81.16%	79.35%	76.04%
Avg. Rel. Returns	-	3.00%	3.25%	3.48%	2.22%	2.64%
Avg. of Positive Rel. Ret.	-	5.07%	5.10%	5.29%	4.12%	4.69%
Outperf. Prob. (5Y)	-	86.98%	86.98%	89.99%	80.42%	85.39%
Max. Rel. Drawdown	-	41.49%	33.29%	32.88%	40.10%	43.46%
3-Y Rolling Vol. Mean	16.55%	13.62%	14.11%	14.93%	13.93%	13.63%
3-Y Rolling Vol. Std Dev	5.49%	4.62%	4.78%	5.15%	4.88%	4.70%
3-Y Rolling Vol. 95%ile	29.34%	24.78%	25.47%	27.89%	26.21%	25.17%
Rel. Ret Bull Markets	-	0.25%	1.90%	2.98%	-0.07%	-0.85%
Rel. Ret Bear Markets	-	7.82%	6.06%	4.86%	6.16%	8.35%
Rel. Ret 25% Bull Mkts	-	-3.94%	0.34%	3.42%	-3.84%	-5.90%
Rel. Ret 25% Bear Mkts	-	7.79%	5.95%	4.59%	6.02%	8.50%
1-Way Ann Turnover	2.7%	34.2%	37.6%	25.0%	30.3%	25.8%

EXHIBIT 7

Comparison of Performance over Last 10 Years.
The analysis is based on daily total returns in USD in the period 31-Dec-2004 to 31-Dec-2014 (10 years). All statistics are annualized. Yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. Reported turnover is one-way annual and it is averaged across all rebalancings in the 10-year period. All allocations are systematically rebalanced quarterly. Maximum relative drawdown is the maximum drawdown of the long-short index whose return is given by the fractional change in the ratio of the strategy index to the benchmark index. Probability of outperformance is the probability of obtaining positive excess returns if one invests in the strategy for a period of 1 (or 3 or 5) years at any point during the history of the strategy. Rolling window of length 1 (or 3 or 5) years and a step size of 1 week is used. Corresponding average relative returns is the average of relative returns across all rolling windows and corresponding average of positive relative returns is the average across rolling windows where the relative returns are positive. Quarters with positive benchmark index returns are bull quarters and the remaining are bear quarters. Top 25% quarters with best benchmark index returns are extreme bull quarters and bottom 25% quarters with worst benchmark index returns are extreme bear quarters. Scientific Beta USA universe contains 500 stocks. The GMV allocation under 1/3 Norm Constraint is based on the 30 underlying strategies which are combinations of six factor tilts (mid-cap, value, high momentum, low volatility, high profitability and low investment) and five diversification-based weighting schemes (Max. Deconcentration, Max Decorrelation, Eff. Min Volatility, Eff. Max Sharpe and Div. Risk Weighted). Source: scientificbeta.com/Scientific Beta USA Long-Term Track Records and Bloomberg.

31-Dec-2004 to 31-Dec-2014 (10 Years)	Sci Beta USA CW	GMV Allocation (Norm 1/3)	Max Deconcentration (90% BM Vol.)	Scientific Beta USA Efficient Min. Volatility	Scientific Beta USA Low Volatility Multi-Strategy	MSCI USA Minimum Volatility
Ann. Returns	7.90%	10.52%	10.66%	10.34%	10.07%	8.96%
Ann. Volatility	20.26%	17.36%	17.90%	17.51%	17.00%	16.91%
Sharpe Ratio	0.32	0.52	0.52	0.51	0.51	0.45
Maximum Drawdown	54.63%	48.36%	48.99%	47.33%	48.31%	46.61%
Ann. Rel. Returns	-	2.61%	2.76%	2.44%	2.17%	1.06%
Tracking Error	-	4.66%	4.22%	4.14%	5.12%	5.20%
Information Ratio	-	0.56	0.65	0.59	0.42	0.20
Outperf. Prob. (1Y)	-	73.62%	78.72%	66.60%	61.49%	44.26%
Avg. Rel. Returns	-	1.96%	2.25%	1.66%	1.40%	0.03%
Avg. of Positive Rel. Ret	-	3.59%	3.61%	3.46%	4.12%	5.12%
Outperf. Prob. (3Y)	-	95.63%	94.81%	93.44%	92.35%	80.05%
Avg. Rel. Returns	-	2.51%	2.67%	2.32%	2.24%	1.61%
Avg. of Positive Rel. Ret	-	2.64%	2.85%	2.52%	2.48%	2.39%
Outperf. Prob. (5Y)	-	100.00%	100.00%	100.00%	100.00%	79.39%
Max Rel. Drawdown	-	7.87%	7.34%	7.51%	8.59%	13.26%
Rel. Ret. Bull Markets	-	-0.74%	0.11%	-1.17%	-2.01%	-4.64%
Rel. Ret. Bear Markets	-	6.82%	5.92%	7.19%	7.97%	9.49%
1-Way Ann Turnover	4.3%	31.6%	36.7%	30.5%	28.7%	- NC

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INDEXES

Relative Risk Allocation with Smart Factor Indexes

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Introduction

Smart beta strategies can have two broad usages in the investment process – as a substitute for cap-weighted benchmarks and as a substitute for active managers. All surveys and studies on smart beta investing show that while many investors have adopted smart beta, not so many think that these smart beta strategies, even when they are in the form of indexes, can replace cap-weighted indexes as a reference for the asset allocation policy[15]. This is not surprising, as the long-standing monopoly and popularity of cap-weighted indexes as benchmarks, owing to their simplicity, are not easy to replace. Smart beta techniques find rather broader application as a complement to cap-weighted indexes and as a substitute for active managers. Ultimately, smart beta is often perceived as a means of improving investment performance in an asset class through diversification, or more recently through factor investing.

When used in its latter role, the comparison between smart beta strategies and active managers becomes unfair because smart beta strategies usually exhibit high levels of tracking error, extreme tracking error, and relative drawdown, while active managers operate under strict, explicit target-tracking-error constraints. Active manager performance appraisal typically pays a great deal of attention to the relative risk budgets that have been used to achieve outperformance. Therefore, in order to truly replace active managers, we require smart beta strategies that are able to respect strict relative-risk targets.

Exhibit 1, Panel A shows that the relative risk of common smart beta strategies is much higher than that of a typical benchmarked manager. The extreme tracking error is in the order of 8-11% and maximum relative drawdown over a 40-year period can be as high as 30-40%. Panel B of Exhibit 1, which displays the relative risk of smart factor indexes over the very long term, shows that the choice of factor exposure, even when accompanied by good diversification of the index that represents it, which is the case with multi-strategy weighting[16], can also lead to higher tracking error and maximum relative drawdown.

EXHIBIT 1

Overview of Relative Risk.
The analysis is based on daily total return data from 12/31/1974 to 12/31/2014 (40 years). The benchmark used is the Scientific Beta USA LTTR CW index. Yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. The Scientific Beta USA LTTR universe contains 500 stocks. Maximum relative drawdown is the maximum drawdown of the long-short index whose return is given by the fractional change in the ratio of the strategy index to the benchmark index. Source: scientificbeta.com/Scientific Beta USA Long-Term Track Records.

Panel A

31-Dec-1974 to 31-Dec-2014 (40 Years)	Scientific Beta USA LTTR				
	Maximum Deconcentration	Diversified Risk Weighted	Maximum Decorrelation	Efficient Minimum Volatility	Efficient Maximum Sharpe Ratio
Ann. Rel. Returns	2.56%	2.57%	2.60%	2.50%	2.87%
Tracking Error	4.12%	4.06%	4.14%	5.09%	4.33%
Max. Relative Drawdown	30.07%	34.10%	30.00%	40.10%	30.66%
3-Y Rolling TE Mean	3.94%	3.74%	4.01%	4.75%	4.08%
3-Y Rolling TE Std Dev	1.37%	1.71%	1.21%	2.06%	1.67%
3-Y Rolling TE 95%ile	7.02%	8.30%	6.99%	10.42%	8.67%

Panel B

31-Dec-1974 to 31-Dec-2014 (40 Years)	Scientific Beta USA LTTR Diversified Multi-Strategy					
	Mid Cap	Momentum	Low Volatility	Value	Low Investment	High Profitability
Ann. Rel. Returns	4.59%	3.49%	2.87%	4.54%	3.89%	3.33%
Tracking Error	6.38%	4.72%	6.04%	5.56%	5.44%	4.39%
Max. Relative Drawdown	42.06%	17.28%	43.46%	32.68%	38.49%	25.21%
3-Y Rolling TE Mean	6.13%	4.53%	5.40%	5.19%	5.07%	4.27%
3-Y Rolling TE Std Dev	2.03%	1.52%	2.97%	2.18%	2.20%	1.29%
3-Y Rolling TE 95%ile	11.00%	7.74%	13.87%	11.20%	11.03%	6.86%

Multi-factor diversification to manage tracking error

In the case of this article, we take six highly liquid Scientific Beta smart factor indexes – Mid-Cap, Value, Momentum, Low Volatility, Low Investment, and High Profitability Diversified Multi-Strategy.[17] The choice of liquidity is guided by the concern to avail of smart indexes that facilitate dynamic risk allocation. Exhibit 2 shows that the systematic risks to which the Scientific Beta smart factor indexes provide consistent exposure are not synchronized, which suggests potential to smooth investment risk by holding a portfolio of single-factor indexes. Low correlations between the relative returns of these indexes suggest that multi-factor solutions will achieve tracking error reduction.

The first multi-factor approach to reduce tracking error is to use a relative equal risk contribution (rel-ERC) allocation. The objective is to equalize ex-ante tracking error risk from each of the underlying components. Thirty highly-liquid factor indexes representing the six systematic risk factors discussed above and five weighting schemes are used for this approach. Weighting scheme diversification is achieved by using five weighting schemes – Maximum Deconcentration, Diversified Risk Weighted, Maximum Decorrelation, Efficient Minimum Volatility and Efficient Maximum Sharpe Ratio. The optimization problem can be specified as follows:

(4)
$$TE(W) = \sqrt{w^T * \Omega * w} \qquad RC_i = w_i \frac{(\Omega * \omega)_i}{\sqrt{w^T * \Omega * w}}$$

(5)
$$RC_i = RC_{ij} \, \forall \, i,j \qquad \begin{cases} \sum_{i=1}^{N} w_i = 1 \\ w_i \geq 0 \, \forall i \end{cases}$$

W_i represents the weight of the *i-th* constituent. RC_i is the contribution of the i-th constituent to portfolio tracking error. N is the number of constituents. Ω is the covariance matrix of total excess returns over the benchmark and is estimated using weekly total returns over the past 104 weeks.

Exhibit 3 shows that the tracking error of a relative-ERC allocation over the entire analysis period is a mere 3.22% and the improved information ratio is 0.86. This approach provides much better results in terms of relative risk (tracking error) management compared to the flagship Scientific Beta Multi-Beta Multi-Strategy EW index, which equalizes the weights of the available indexes. In order to analyze the time variation of tracking error, we also look at tracking error over three-year rolling windows. Although this approach is successful in bringing down the average level of tracking error, it does not guarantee explicit control of tracking error. The 95% worst 3-year tracking error of relative-ERC allocation is 5.89% while the standard deviation is 1.09%. The maximum relative drawdown (with respect to a broad cap-weighted index) of this strategy is reduced to 14.82%. This is far below the level of maximum relative drawdown of traditional smart beta strategies, but still counts as sizeable underperformance for a benchmarked manager.

Core-satellite approach

As discussed before, the tracking error budgets of benchmarked active managers are smaller and therefore the multi-factor diversification solution is not a viable approach in its present form. However, in order to manage tighter tracking budgets, one must impose explicit tracking-error constraints by using the core-satellite approach. In this approach, we combine an optimized satellite portfolio whose tracking error is well behaved – the relative ERC allocation with the core portfolio, the broad cap-weighted index (Amenc et al. (2012)).

In this example, we construct four portfolios with target tracking errors of 2.0%, 1.5%, 1.0%, and 0.50% respectively. The ratio in which core and satellite are combined quarterly is determined by the two-year ex-ante tracking error of the satellite and a buffer tracking error.

[15] *See for example Amenc, N., F. Goltz, V. Le Sourd and A. Lodh, July 2015, Alternative Equity Beta Investing: a Survey, EDHEC-Risk Institute Publication (p. 137), produced with the support of SGCIB (Newedge).*

[16] *Multi-strategy draws on the following smart beta weighting schemes: Maximum Deconcentration, Diversified Risk Weighted, Maximum Decorrelation, Efficient Maximum Sharpe Ratio and Efficient Minimum Volatility. For more information, please refer to the Scientific Beta Diversified Multi-Strategy Index white paper.*
http://docs.edhec-risk.com/mrk/000000/Scientific_Beta_Library/External_use/White_papers/ERI_Scientific_Beta_Publication_Scientfic_Beta_Diversified_Multi-Strategy_Index.pdf"

[17] *The following selection rules are applied to select stocks for each tilt: Mid Cap: bottom 50% free-float-adjusted market-cap stocks are selected. Value: top 50% stocks are selected by book-to market (B/M) ratio. B/M is defined as the ratio of available book value of shareholders' equity to company market cap; High Momentum: top 50% stocks are selected by returns over past 52 weeks, minus the last 4 weeks; Low Volatility: bottom 50% stocks are selected by their standard deviation of weekly stock returns over the past 104 weeks; High Profitability: top 50% stocks with highest Gross Profit/Total Asset ratio are selected; Low Investment: bottom 50% stocks with least 2-Year total asset growth rate are selected. This score-based selection is done twice a year (June and December) for Momentum and once a year (June) for the other three factors. The "highly liquid" version of the indexes picks the 60% of stocks with the highest liquidity score amongst the stocks resulting from factor selection.*

(6) $$Ratio_{Satellite} = \frac{TE_{target}}{TE_{2\text{-}Y\ ex\ ante} + TE_{buffer}}$$

(7) $$TE_{2\text{-}Y\ ex\ ante} = \sqrt{w^T * \Omega * w}$$

W is the optimized weights of constituent indexes. Ω is the covariance matrix of total excess returns over the benchmark and is estimated using weekly total returns over the past 104 weeks. The buffer tracking error is a fixed long-term parameter that is calibrated only once. We calibrate it over the time period of the first 10 years (31-Dec-1974 to 31-Dec-1984). The buffer tracking error is the average three-year rolling tracking error observed over this period.

It should be noted that the allocation between core and satellite portfolios is dynamic in nature and allocates more weight to the satellite when its ex-ante tracking error goes down, thereby making efficient use of the relative risk budget. Exhibit 4 shows that the core-satellite approach is indeed successful in respecting the target tracking error ex-post. For example, the '1% Target' portfolio's three-year rolling TE averages at 0.91% with a standard deviation of 0.20%. Despite a low tracking-error budget, the strategy delivers a strong probability of outperformance – 84% for a three-year investment horizon.

Improved management of tracking error

The approach described above, due to the relative importance of the variation in tracking error (the average value of tracking error of the Relative ERC satellite over a period of 3 years is 3.07%, but the standard deviation of the tracking error over the same period is 1.09%, so the tracking error could be higher), led necessarily to underexposure to the satellite ex-ante in order to take account of the volatility of the tracking error ex-post. In addition, even when underexposing to the satellite, the ex-post tracking error could be quite high, as the measure of extreme tracking error shows.

The approach proposed here aims to control the volatility of the satellite's tracking error better in order to improve the core-satellite allocation, by reducing the ex-ante weighting of the satellite compared to what it would have been if the ex-ante tracking error were representative of the ex-post tracking error, and to reduce the risk of extreme tracking error.

In order to manage tracking error in an efficient manner, one must understand that the tracking error (TE) risk is made up of two components – systematic TE and idiosyncratic TE. In order to outperform the cap-weighted (CW) benchmark, the portfolio has to seek risk factors that are different from those of the benchmark. This excess exposure to risk factors that are systematically rewarded in the long term becomes a source of tracking error. This variety of tracking error is termed systematic TE and since it is rewarded in nature it is desired tracking error.

The tracking error that cannot be explained by the exposure to systematic risk factors is unrewarded and therefore is undesired. This unrewarded or idiosyncratic TE can of course be reduced by good diversification of the satellite or its components. For example, the smart factor index approach proposed by Scientific Beta enables this idiosyncratic risk to be reduced substantially in comparison with traditional factor indexes, which are often highly concentrated. Moreover, the multi-smart-factor allocation also allows this TE to be reduced.

Exhibit 5 compares the idiosyncratic TE of an array of factor-tilted indexes in Panel A and that of single-factor indexes and multi-factor indexes in Panel B. Panel A shows that the idiosyncratic TE increases as concentration increases, since factor-tilted portfolios constructed on 20% of stocks have more idiosyncratic TE than those constructed on 50% of stocks. Panel B shows that the idiosyncratic TE of the equal-weighted multi-factor index is far below the average idiosyncratic TE of its components.

However we must recognize that even if we can reduce the idiosyncratic TE, there is also a choice of difference in systematic risk that is implicit and does not necessarily correspond to the choice of rewarded factors. It is that of the systematic market factor. In fact the majority of smart beta strategies have a market beta of less than 1. This difference in market beta has a strong influence on the tracking error of the strategy. Most smart beta strategies have betas that are lower than 1, which explains moreover why their performance is often better in bull markets than in bear markets. Quite apart from the problem of tracking error, one could argue that since it involves multi-factor indexes, there is a contradiction in seeking exposure to rewarded factors and at the same time not being fully invested in the market factor, which corresponds to a first-order risk premium in comparison with the premia associated with the other factors.

EXHIBIT 2

Correlation of Excess Returns.
The analysis is based on daily total return data from 12/31/1974 to 12/31/2014 (40 years). The benchmark used is the Scientific Beta USA LTTR CW index. Yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. The Scientific Beta USA LTTR universe contains 500 stocks. Source: scientificbeta.com/Scientific Beta USA Long-Term Track Records.

PANEL A – Unconditional Correlation

31-Dec-1974 to 31-Dec-2014 (40 Years)	Scientific Beta Highly Liquid Diversified Multi-Strategies				
	High Momentum	Low Volatility	Value	Low Investment	High Profitability
Mid Cap	0.35	0.31	0.71	0.62	0.41
High Momentum		0.32	0.40	0.50	0.42
Low Volatility			0.52	0.74	0.29
Value				0.71	0.15
Low Investment					0.39

PANEL B – Conditional Correlation: Bull Markets

31-Dec-1974 to 31-Dec-2014 (40 Years)	Scientific Beta Highly Liquid Diversified Multi-Strategies				
	High Momentum	Low Volatility	Value	Low Investment	High Profitability
Mid Cap	0.37	0.28	0.70	0.62	0.45
High Momentum		0.30	0.41	0.47	0.38
Low Volatility			0.48	0.68	0.23
Value				0.70	0.16
Low Investment					0.34

PANEL C – Conditional Correlation: Bear Markets

31-Dec-1974 to 31-Dec-2014 (40 Years)	Scientific Beta Highly Liquid Diversified Multi-Strategies				
	High Momentum	Low Volatility	Value	Low Investment	High Profitability
Mid Cap	0.33	0.33	0.73	0.61	0.37
High Momentum		0.35	0.39	0.53	0.48
Low Volatility			0.57	0.81	0.35
Value				0.71	0.14
Low Investment					0.46

EXHIBIT 3

Relative ERC Allocation Performance.
The analysis is based on daily total returns in USD in the period 31-Dec-1974 to 31-Dec-2014 (40 years). All statistics are annualized. Yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. Reported turnover is one-way annual and it is averaged across 160 rebalancings in the 40-year period. All allocations are systematically rebalanced quarterly. Maximum relative drawdown is the maximum drawdown of the long-short index whose return is given by the fractional change in the ratio of the strategy index to the benchmark index. Quarters with positive benchmark index returns are bull quarters and the remaining are bear quarters. The top 25% quarters with the best benchmark index returns are extreme bull quarters and the bottom 25% quarters with the worst benchmark index returns are extreme bear quarters. The Scientific Beta USA LTTR universe contains 500 stocks. The MBMS EW and Rel-ERC strategies are based on 30 underlying strategies which are combinations of six factor tilts (mid-cap, value, high momentum, low volatility, high profitability and low investment) and five diversification-based weighting schemes (Max. Deconcentration, Max Decorrelation, Eff. Min Volatility, Eff. Max Sharpe and Div. Risk Weighted). Post stock selection, we apply a high-liquidity filter which selects the most liquid constituents (60% most liquid stocks) among the stocks that belong to one of the available stock selections. Source: scientificbeta.com/Scientific Beta USA Long-Term Track Records.

31-Dec-1974 to 31-Dec-2014 (40 Years)	Broad CW Index	Scientific Beta US LTTR HLiq MBMS EW	Scientific Beta US LTTR HLiq Rel.-ERC
Ann. Returns	12.16%	15.36%	14.93%
Ann. Volatility	17.12%	16.01%	16.17%
Sharpe Ratio	0.41	0.64	0.61
Maximum Drawdown	54.53%	52.85%	52.77%
Ann. Rel. Returns	-	3.21%	2.77%
Tracking Error	-	3.84%	3.22%
Information Ratio	-	0.83	0.86
Max. Relative Drawdown	-	23.82%	14.82%
3-Y Rolling TE Mean	-	3.56%	3.07%
3-Y Rolling TE Std Dev	-	1.58%	1.09%
3-Y Rolling TE 95%ile	-	8.04%	5.89%
Rel. Ret. Bull Markets	-	2.78%	2.72%
Rel. Ret. Bear Markets	-	3.58%	2.63%
Rel. Ret. 25% Bull Markets	-	2.90%	3.24%
Rel. Ret. 25% Bear Markets	-	3.48%	2.42%
1-Way Ann. Turnover	2.7%	28.3%	29.9%

EXHIBIT 4

Core-Satellite Portfolio Performance.
The table below presents the results of a core-satellite approach wherein the core is represented by SciBeta Long-Term United States Cap-Weighted and the satellite is represented by SciBeta Long-Term United States HLiq Rel-ERC. The analysis is based on daily total returns in USD in the period 31-Dec-1974 to 31-Dec-2014 (40 years). All statistics are annualized. Yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. Reported turnover is one-way annual and it is averaged across 160 rebalancings in the 40-year period. All allocations are systematically rebalanced quarterly. Maximum relative drawdown is the maximum drawdown of the long-short index whose return is given by the fractional change in the ratio of the strategy index to the benchmark index. Probability of outperformance is the probability of obtaining positive excess returns if one invests in the strategy for a period of 1 (or 3 or 5) years at any point during the history of the strategy. Rolling window of length 1 (or 3 or 5) years and a step size of 1 week is used. Corresponding Average Relative Returns is the average of relative returns across all rolling windows and corresponding Average of Positive Relative Returns is the average across rolling windows where the relative returns are positive. Quarters with positive benchmark index returns are bull quarters and the remaining are bear quarters. The top 25% quarters with the best benchmark index returns are extreme bull quarters and the bottom 25% quarters with the worst benchmark index returns are extreme bear quarters. The Scientific Beta USA LTTR universe contains 500 stocks. Source: scientificbeta.com/Scientific Beta USA Long-Term Track Records.

31-Dec-1974 to 31-Dec-2014 (40 Years)	Broad CW Index	0.5% Target TE	1.0% Target TE	1.5% Target TE	2.0% Target TE	Scientific Beta US LTTR HLiq Rel-ERC
Ann. Returns	12.16%	12.51%	12.86%	13.21%	13.56%	14.93%
Ann. Volatility	17.12%	16.95%	16.80%	16.65%	16.52%	16.17%
Sharpe Ratio	0.41	0.44	0.46	0.49	0.51	0.61
Maximum Drawdown	54.53%	54.20%	53.86%	53.52%	53.18%	52.77%
Ann. Rel. Returns	-	0.35%	0.70%	1.05%	1.40%	2.77%
Tracking Error	-	0.46%	0.92%	1.38%	1.84%	3.22%
Information Ratio	-	0.77	0.77	0.76	0.76	0.86
Outperf. Prob. (1Y)	-	76.33%	76.33%	76.28%	76.28%	76.03%
Average Rel. Returns	-	0.33%	0.66%	0.99%	1.32%	2.62%
Average of Positive Rel. Ret	-	0.56%	1.13%	1.70%	2.27%	4.19%
Outperf. Prob. (3Y)	-	83.70%	83.70%	83.64%	83.64%	84.11%
Average Rel. Returns	-	0.32%	0.64%	0.96%	1.28%	2.56%
Average of Positive Rel. Ret	-	0.46%	0.92%	1.38%	1.83%	3.45%
Outperf. Prob. (5Y)	-	89.00%	88.89%	88.84%	88.79%	90.97%
Max. Relative Drawdown	-	2.64%	5.21%	7.73%	10.19%	14.82%
3-Y Rolling TE Mean	-	0.46%	0.91%	1.37%	1.83%	3.07%
3-Y Rolling TE Std Dev	-	0.10%	0.20%	0.30%	0.40%	1.09%
3-Y Rolling TE 95%ile	-	0.61%	1.21%	1.82%	2.42%	5.89%
1-Way Ann. Turnover	2.7%	7.9%	12.0%	16.4%	21.0%	29.9%

In order to deal with the problem of low market beta, we propose another multi-factor approach that neutralizes beta bias – Maximum Deconcentration with a constraint of unitary market beta. The optimization problem can be written as:

(8)
$$w^* = ar\,gmax\{1/(w^T * w)\} \begin{cases} \sum_{i=1}^{N} w_i = 1 \\ w_i \geq 0 \forall_i \\ beta = \frac{Cov[(R^* w)_i R_{CW}]}{Var(R_{CW})} = 1 \end{cases}$$

W_i represents the weight of the *i-th* constituent. R_{CW} is benchmark returns and R is component returns. N is the number of constituents. Beta is estimated using weekly total returns over the past 104 weeks.

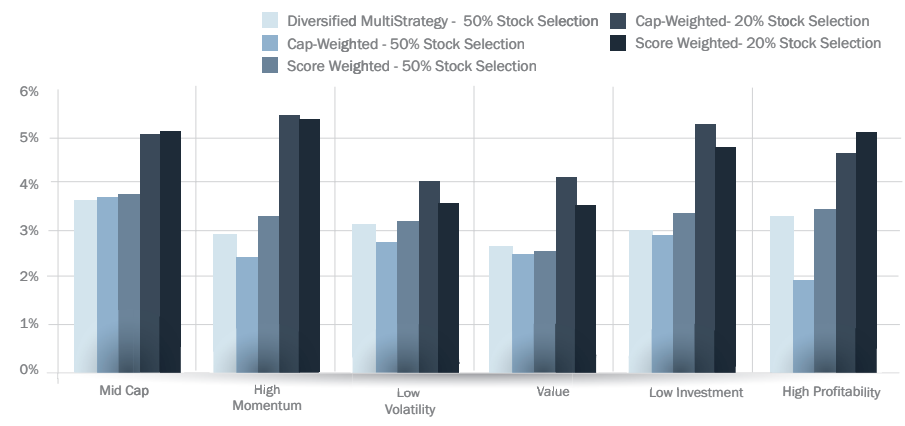
Exhibit 6 shows that beta-constrained maximum deconcentration achieves low tracking error with an improved information ratio (0.91). Compared to the flagship Scientific Beta US LTTR MBMS EW, the improvement in information ratio is 9.64%, with a reduction in TE from 3.84% to 3.26%. The most striking feature of this allocation is its maximum relative drawdown, which is 7.30% compared to 23.82% for the equal-weighted allocation. Due to market beta constraints, the strategy does not fall short on performance when the markets are bullish like most smart beta strategies do. The standard deviation and 95th percentile of 3-year rolling tracking error also show improvement, meaning that tracking error is more stable over time. Its "well-behaved" tracking error makes it a good candidate for a satellite in core-satellite allocations.

In conclusion, we find that value, in terms of risk-adjusted relative performance, can be added through allocation across smart factor indexes, for investors with a tracking error budget. The favorable factor tilts generate outperformance and two-fold diversification, one across factors and another across weighting schemes, reducing tracking error. As a result, extremely substantial levels of relative risk-adjusted outperformance can be achieved. Implementation of an allocation that guarantees a level of market beta equivalent to that of a cap-weighted index allows the benefits of this relative risk diversification to be optimized. Exhibit 7 shows that this dynamic allocation between smart factor indexes can be combined with a core-satellite approach to limit the tracking error to desired levels, as low as 0.5%, while maintaining high information ratios. •

EXHIBIT 5

Idiosyncratic Tracking Error Comparison.
The analysis is based on daily total return data from 12/31/1974 to 12/31/2014 (40 years). The Mid-Cap, High Momentum, Low Volatility, Value, Low Investment and High Profitability selections represent the 50%/20% of stocks with such characteristics in a US universe of 500 stocks. The Carhart four-factor model is used. The market, size, value and momentum factors for the USA universe available online in Kenneth French's data library are used. Yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. The Scientific Beta USA LTTR universe contains 500 stocks. Source: scientificbeta.com/Scientific Beta USA Long-Term Track Records.

PANEL A – Diversified versus Concentrated Factor Indexes



PANEL B – Single Beta versus Multi-Beta Factor Indexes

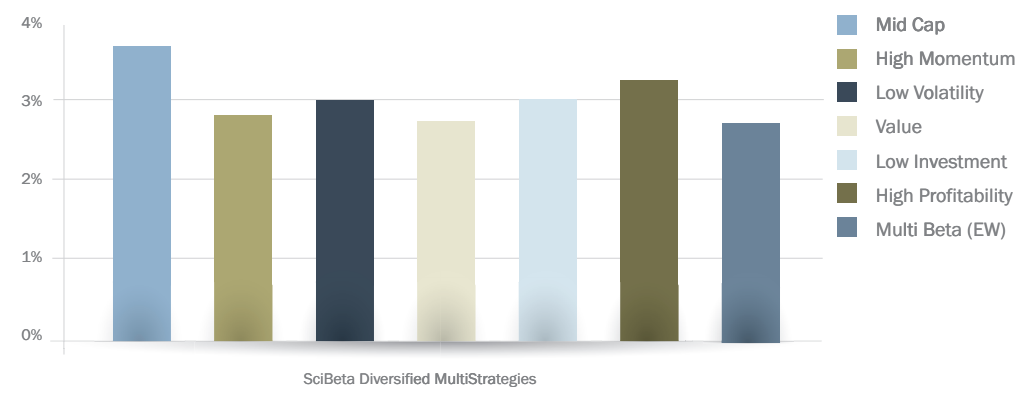


EXHIBIT 6

Maximum Deconcentration (beta=1) Allocation Performance.
The analysis is based on daily total returns in USD in the period 31-Dec-1974 to 31-Dec-2014 (40 years). All statistics are annualized. Yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. Reported turnover is one-way annual and it is averaged across 160 rebalancings in the 40-year period. All allocations are systematically rebalanced quarterly. Maximum relative drawdown is the maximum drawdown of the long-short index whose return is given by the fractional change in the ratio of the strategy index to the benchmark index. Quarters with positive benchmark index returns are bull quarters and the remaining are bear quarters. The top 25% quarters with the best benchmark index returns are extreme bull quarters and the bottom 25% quarters with the worst benchmark index returns are extreme bear quarters. The Scientific Beta USA LTTR universe contains 500 stocks. The MBMS EW and Rel-ERC strategies are based on 30 underlying strategies which are combinations of six factor tilts (mid-cap, value, high momentum, low volatility, high profitability and low investment) and five diversification-based weighting schemes (Max. Deconcentration, Max Decorrelation, Eff. Min Volatility, Eff. Max Sharpe and Div. Risk Weighted). Post stock selection, we apply a high-liquidity filter which selects the most liquid constituents (60% most liquid stocks) among the stocks that belong to one of the available stock selections. The last column presents results of another approach that neutralizes beta bias - Maximum Deconcentration with a constraint of unitary market beta. Source: scientificbeta.com/Scientific Beta USA Long-Term Track Records.

31-Dec-1974 to 31-Dec-2014 (40 Years)	Broad CW Index	HLiq MBMS EW	HLiq MBMS Rel.-ERC	Scientific Beta US LTTR HLiq Max Deconc. (beta=1)
Ann. Returns	12.16%	15.36%	14.93%	15.11%
Ann. Volatility	17.12%	16.01%	16.17%	16.87%
Sharpe Ratio	0.41	0.64	0.61	0.59
Maximum Drawdown	54.53%	52.85%	52.77%	53.59%
Ann. Rel. Returns	-	3.21%	2.77%	2.95%
Tracking Error	-	3.84%	3.22%	3.26%
Information Ratio	-	0.83	0.86	0.91
Max. Relative Drawdown	-	23.82%	14.82%	7.30%
CAPM Market Beta	-	0.91	0.93	0.97
Carhart Market Beta	-	0.93	0.94	0.99
3-Y Rolling TE Mean	-	3.56%	3.07%	3.17%
3-Y Rolling TE Std Dev	-	1.58%	1.09%	0.93%
3-Y Rolling TE 95%ile	-	8.04%	5.89%	5.20%
Rel. Ret. Bull Markets	-	2.78%	2.72%	4.15%
Rel. Ret. Bear Markets	-	3.58%	2.63%	1.00%
Rel. Ret. 25% Bull Markets	-	2.90%	3.24%	6.90%
Rel. Ret. 25% Bear Markets	-	3.48%	2.42%	0.64%
1-Way Ann. Turnover	2.7%	28.3%	29.9%	40.2%

EXHIBIT 7

Core-Satellite Portfolio Performance Summary.
The table below presents the results of a core-satellite approach wherein the core is represented by SciBeta Long-Term United States Cap-Weighted and the satellite is represented by an approach that neutralizes beta bias - Maximum Deconcentration with a constraint of unitary market beta. The analysis is based on daily total returns in USD in the period 31-Dec-1974 to 31-Dec-2014 (40 years). All statistics are annualized. Yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. Reported turnover is one-way annual and it is averaged across 160 rebalancings in the 40-year period. All allocations are systematically rebalanced quarterly. 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. The Scientific Beta USA LTTR universe contains 500 stocks. Source: scientificbeta.com/Scientific Beta USA Long Term Track Records.

31-Dec-1974 to 31-Dec-2014 (40 Years)	Broad CW Index	0.5% Target TE	1.0% Target TE	1.5% Target TE	2.0% Target TE	Scientific Beta US LTTR Max Deconc (beta=1)
Ann. Returns	12.16%	12.52%	12.89%	13.25%	13.61%	15.11%
Ann. Volatility	17.12%	17.05%	16.99%	16.95%	16.91%	16.87%
Sharpe Ratio	0.41	0.43	0.46	0.48	0.50	0.59
Maximum Drawdown	54.53%	54.36%	54.20%	54.03%	53.87%	53.59%
Ann. Rel. Returns	-	0.36%	0.73%	1.09%	1.45%	2.95%
Tracking Error	-	0.43%	0.86%	1.29%	1.72%	3.26%
Information Ratio	-	0.85	0.85	0.85	0.84	0.91
Max. Relative Drawdown	-	1.17%	2.33%	3.48%	4.63%	7.30%
3-Y Rolling TE Mean	-	0.43%	0.85%	1.28%	1.71%	3.17%
3-Y Rolling TE Std Dev	-	0.09%	0.18%	0.27%	0.36%	0.93%
3-Y Rolling TE 95%ile	-	0.59%	1.19%	1.78%	2.37%	5.20%
1-Way Ann Turnover	2.7%	8.8%	13.9%	19.3%	24.8%	40.2%

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Lodh, A. and S. Sivasubramanian. *2015. Scientific Beta Diversified Multi-Strategy Index. ERI Scientific Beta Publication.*

3.95%

is the average annual long-term outperformance observed with US data over 40 years of the Scientific Beta US Multi-Beta Multi-Strategy EW Index compared to a reference index based on the 500 largest market-cap US stocks.

This index equalises the investment in four extremely well-diversified smart factor indices (Value, Momentum, Mid-Cap and Low Volatility).

It combines the best of factor investing with the best of smart beta and has improved the Sharpe ratio with respect to a reference index based on the 500 largest market-cap US stocks by 71%* over the last 40 years.

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www.scientificbeta.com

*Overall percentage increase in Sharpe ratio observed between December 31, 1974 and December 31, 2014 (40 years) for the long-term track record Scientific Beta US Multi-Beta Multi-Strategy EW index compared to its cap-weighted equivalent calculated on a universe of the 500 largest-capitalisation US stocks. All the details on the calculations and the indices are available on the www.scientificbeta.com website.

INDEXES

The Limitations of Factor Investing: Impact of the Volkswagen Scandal on Concentrated versus Diversified Factor Indexes

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Volkswagen has been caught up in one of the most notorious scandals in corporate history by installing cheat software to reduce emissions during testing. The news broke on the eve of Friday, September 18, 2015 and the stock markets penalized Volkswagen AG and other automobile stocks, including suppliers, heavily on Monday, September 21, 2015. Volkswagen AG fell around 20% on the Monday. Indexes that are heavily concentrated in automobile stocks, including Volkswagen AG, suffered huge losses. As we have emphasized on many occasions, the question of diversification is key for smart beta offerings. In recent years, we have unfortunately seen the emergence of factor indexes which, in order to have the strongest exposure to these factors, have favored concentration, with weightings that did not genuinely take the necessary diversification of specific risk into account, preferring to look for the best factor score. We show in the present article that this choice of factor concentration has led many factor indexes to hold Volkswagen AG, and more globally automobile stocks, in large quantities, and ultimately to incur definite losses in the month of September 2015. Conversely, Scientific Beta's multi-smart-factor indexes, through their construction philosophy, which distinguishes the choice of factor exposures from the implementation of a diversification method, do not suffer from this difficulty. Given their well diversified nature, SciBeta Multi-Beta Multi-Strategy indexes were able to limit their losses and outperform the concentrated cap-weighted indexes.

This analysis digs deep into the impact of the scandal on the Stoxx Europe 600 cap-weighted index, the SciBeta Extended Europe Multi-Beta Multi-Strategy EW index and the Score-Weighted Multi-Beta Extended Europe strategy. The SciBeta Extended Europe Multi-Beta Multi-Strategy EW index is the equal-weighted combination of four factor-tilted multi-strategy indexes – Mid Cap, High Momentum, Low Volatility and Value. Each factor-tilted multi-strategy index selects 50% of stocks from the universe based on the factor score. The multi-strategy weighting scheme is the equal-weighted combination of five weighting schemes: Maximum Deconcentration, Maximum Decorrelation, Efficient Minimum Volatility, Efficient Maximum Sharpe Ratio and Diversified Risk Weighted[18].

The score-weighted multi-beta EW strategy on the other hand is the equal-weighted combination of the four factor-tilted score-weighted indexes – Mid Cap, High Momentum, Low Volatility and Value. Each factor-tilted score-weighted index selects 50% of stocks from the universe based on the factor score. The portfolios are rebalanced once every quarter – on the third Friday of March/June/September/December, coinciding exactly with the quarterly rebalancing dates of Scientific Beta. The weights on each rebalancing date of the score-weighted indexes are given by

$$w_i * S_i$$

where w_i is the market cap-weight of the i-th stock and, S_i is the S_score for the relevant factor, calculated from the Z_score, which is winsorized at 3 and -3 (i.e., $z\_score > 3$ is set equal to 3 and $z\_score < -3$ is set equal to -3) and is given by,

$$S\_Score = \begin{cases} 1 + z\_score, if\ z\_score \geq 0 \\ \frac{1}{1 - z\ score}, if\ z\ score > 0 \end{cases}$$

In total, 13 stocks are identified to be in the automobile and auto parts sub-sector of the Cyclical Consumer Goods sector based on the Thomson Reuters Business Classification (TRBC) in the Extended Europe universe. Volkswagen AG is one of these. All 13 stocks are listed below in Exhibit 1. The SciBeta indexes were last rebalanced on September 18, 2015 (systematic quarterly review on the third Friday of June/September/December/March) just before the scandal broke out.

Exhibit 1 below lists the 13 automobile and related stocks and the corresponding weights as of the rebalancing date in the three indexes. It is clear that the SciBeta Extended Europe Multi-Beta Multi-Strategy EW index gives the least weight to the automobile stocks compared to the cap-weighted Stoxx Europe 600 index or the score-weighted multi-beta strategy. The SciBeta Extended Europe Multi-Beta Multi-Strategy EW index underweights the auto stocks by 1.40%. This is very significant given that the Extended Europe universe consists of 600 stocks in total. In the Stoxx Europe 600 index just 13 stocks represent 2.77% of the index. The score-weighted multi-beta index has 2.15% in auto stocks. It underweights the auto stocks slightly relative to the cap-weighted Stoxx Europe 600, but overweights them with respect to the SciBeta Extended Europe Multi-Beta Multi-Strategy EW index. Volkswagen AG alone has been given a mere weight of 0.05% in the case of SciBeta Extended Europe Multi-Beta Multi-Strategy EW, compared to the 0.34% of the Stoxx Europe 600. The score-weighted multi-beta index attributes 0.11%.

Since we underweight the stocks in the auto sector, the impact of losses in the SciBeta Extended Europe Multi-Beta Multi-Strategy EW index is minimal.

For the period September 18, 2015 to September 25, 2015, the two indexes (Stoxx Europe 600 and SciBeta Extended Europe Multi-Beta Multi-Strategy EW) and the Score-Weighted Multi-Beta EW strategy posted cumulative performance of -3.29%, -2.79% and -3.39% respectively. The SciBeta Extended Europe Multi-Beta Multi-Strategy EW index outperformed by 50 bps in the 7-day period, whereas the score-weighted multi-beta strategy underperformed by 10 bps. For the same factor definitions and the same allocation to those factors, we therefore see clearly that the effect of diversifying specific risk is considerable.

If we look at the auto stocks effect over the period, the weighted-average total returns that attribute losses to the 13 auto stocks whose weights are taken from the corresponding Stoxx Europe 600 and SciBeta Extended Europe Multi-Beta Multi-Strategy EW indexes, and the Score-Weighted Multi-Beta EW strategy, are losses of 38 bps, 14 bps, and 28 bps respectively in the 7-day period. The 13 auto stocks in the SciBeta Extended Europe Multi-Beta Multi-Strategy EW index outperformed by 24 bps, which represented approximately 50% of the total outperformance posted by the index relative to the Stoxx Europe 600. Volkswagen AG alone is responsible for outperformance of 10 bps in the case of the SciBeta Extended Europe Multi-Beta Multi-Strategy EW index. The score-weighted strategy posts an auto sector outperformance of 10 bps because it underweights auto stocks, although the index underperforms the Stoxx Europe 600 overall. Volkswagen AG contributes to 8 bps out of the 10 bps outperformance in the case of the score-weighted multi-beta strategy. Given the number of stocks taken into account (with the

> The fact that a factor index whose specific risks are well-diversified has resisted the Volkswagen scandal well is important.

[18] *Details on the MBMS approach can be found in the white paper Scientific Beta Multi-Beta Multi-Strategy Indices: Implementing Multi-Factor Equity Portfolios with Smart Factor Indices. The conceptual framework for smart beta indexes, distinguishing the choice of factor exposure from the weighting, was the subject of a publication in the Journal of Portfolio Management: Amenc N., F. Goltz and A. Lodh. Fall 2012. Choose Your Betas: Benchmarking Alternative Equity Index Strategies. Journal of Portfolio Management, Vol. 39, No. 1*

factors being defined on the basis of 50% of the universe), multi-factor score-weighted investment nonetheless managed to limit the excessive concentration in the German automobile sector.

If we now examine other forms of multi-factor indexes that have marketed the performance that can be achieved through strong exposure to factors, and have been less concerned about diversification of specific risk, we note that the exposure to Volkswagen AG risk is considerable. We observe for example that the J.P. Morgan Multi-Factor Europe index was very strongly exposed to the risk of the Volkswagen AG stock, as was the MSCI Europe Diversified Multi Factor index. As such, these indexes respectively contained almost one and a half times and over two times more Volkswagen AG stock than the Stoxx Europe 600, and almost 10 times and 16 times more Volkswagen AG stock than the Scientific Beta Extended Europe Multi-Beta Multi-Strategy EW index. Since they contain a lower number of stocks than the score-weighted strategy analyzed previously, these indexes do not benefit from a deconcentration effect that can be observed in the broad score-weighted indexes.

As we have already emphasized in a previous article (Amenc N., F. Goltz and S. Sivasubramanian, August 2015, Concentrated vs. Diversified Factors, EDHEC-Risk Institute Research for Institutional Money Management supplement to Pensions & Investments, Volume 1, Number 7), we feel that the diversification of specific risk is the most overlooked dimension of the new factor approaches. It is unfortunately not sufficient to allocate to different factors in order to have a well-diversified portfolio; it is also necessary to take account of other unrewarded risks that are present in the portfolio, whether involving risks that are firm-specific (idiosyncratic risk) or more systematic risks (macroeconomic sector, currency or commodity risk exposures). It is therefore possible to hold a good benchmark in the factor sense of the term while not meeting the objectives of specific risk diversification.

Ultimately, the poor diversification of their specific risks led these indexes to underperform the SciBeta Extended Europe Multi-Beta Multi-Strategy EW index considerably, with excess returns compared to the Stoxx Europe 600 index for the month of September of -0.47% for the Lyxor J.P. Morgan Multi-Factor Europe index and 0.59% for MSCI Diversified Multi Factor Europe, compared to 1.47% for the SciBeta Extended Europe Multi-Beta Multi-Strategy EW index.

The analysis of the Volkswagen case also provides a good understanding of how the search for strong factor exposure can lead to overconcentration in a particular stock. Panel C of Exhibit 1 provides the weights of Volkswagen AG across constituent factor indexes. Volkswagen AG is a Value stock and had only been included in the Value factor-tilted indexes. We can see from this illustration that even when one diversifies across factors, there is a risk of being exposed to a specific risk when the factors themselves are poorly diversified.

It is important to emphasize moreover that factor indexes which sought this strong exposure, whether score-weighted or more globally target-factor-exposure-weighted, not only contained a high proportion of Volkswagen stock, but logically, if we stick with the implementation of their ground rules, will have a tendency to increase the weight of this stock, because its considerable depreciation is making it an increasingly "Value" stock. The same phenomenon had been observed during the financial crisis of 2008 or the Greek sovereign crisis when indexes weighted according to fundamental attributes or factor scores tended to favor financial or Greek stocks given the dichotomy that existed between the evolution of prices, which reflect the information available, and accounting attributes, which are backward-looking by definition. Ultimately, this type of approach, which targets index concentration on the basis of fundamental indicators, or scores involving fundamental indicators, as is the case for Value, leads investors to make bets on themes that are not necessarily those that are explicitly proposed by the index: in 2008, the possibility of banks being saved by the States, in 2011 the Euro zone being saved, and in the case of Volkswagen, the firm's resistance to the scandal and probably a bet on the size of the fines that will actually be applied to the firm.

Value indexes – comparison

In this section, we assess the impact of the Volkswagen scandal on Value-tilted indexes, since Volkswagen AG is a Value stock, as seen in Panel C of Exhibit 1. Exhibit 2 presents the weights and performance attribution to Volkswagen AG and other automobile stocks in Value-tilted cap-weighted,

EXHIBIT 1

Impact of Volkswagen Scandal on Stoxx Europe 600 vs SciBeta MBMS Index and Score-Weighted Multi-Beta Strategy. Analysis is based on weekly total returns in USD from 18-Sept-2015 to 25-Sept-2015 on the Extended Europe universe. Auto and Auto Parts sector stocks are obtained as per Thomson Reuters Business Classification codes. The SciBeta Extended Europe Multi-Beta Multi-Strategy EW index is the equal-weighted combination of the four factor-tilted multi-strategy indexes – Mid Cap, High Momentum, Low Volatility and Value. Each factor-tilted multi-strategy index selects 50% of stocks from the universe based on the factor score. The multi-strategy weighting scheme is the equal-weighted combination of 5 weighting schemes: Maximum Deconcentration, Maximum Decorrelation, Efficient Minimum Volatility, Efficient Maximum Sharpe Ratio and Diversified Risk Weighted. The score-weighted multi-beta EW strategy on the other hand is the equal-weighted combination of the four factor-tilted score-weighted indexes – Mid Cap, High Momentum, Low Volatility and Value. Each factor-tilted score-weighted index selects 50% of stocks from the universe based on the factor score.

PANEL A – Volkswagen AG

Weight Analysis			
Weights as of Rebalancing Date 18-Sept-2015	Weights as of Rebalancing Date 18-Sept-2015		
Auto Stocks that are part of Extended Europe Universe	Stoxx Europe 600	SciBeta Extended Europe Multi-Beta Multi-Strategy EW	Multi-Beta Score Weighted EW
'Volkswagen AG'	0.34%	0.05%	0.11%
Active Weights	-	-0.29%	-0.23%
Cumulative Returns	-3.29%	-2.79%	-3.39%
Cumulative Excess Returns	-	0.50%	-0.10%
Weighted Cumulative Returns of Volkswagen AG	-0.12%	-0.02%	-0.04%
Weighted Cumulative Excess Returns of Volkswagen AG	-	0.10%	0.08%
Percentage of Outperformance because of Underweighted Volkswagen AG	-	20.70%	-

PANEL B – Other Automobile and Auto Parts Stocks

Weight Analysis			
Weights as of Rebalancing Date 18-Sept-2015	Weights as of Rebalancing Date 18-Sept-2015		
Auto Stocks that are part of Extended Europe Universe	Stoxx Europe 600	SciBeta Extended Europe Multi-Beta Multi-Strategy EW	Multi-Beta Score Weighted EW
'Valeo SA'	0.12%	0.04%	0.06%
'Renault Société Anonyme'	0.20%	0.07%	0.19%
'Porsche Automobil Holding SE'	0.12%	0.04%	0.19%
'Pirelli & C. SpA'	0.06%	0.26%	0.13%
'Peugeot S.A.'	0.09%	0.16%	0.21%
'Nokian Renkaat Oyj'	0.05%	0.05%	0.08%
'Fiat Chrysler Automobiles N.V.'	0.15%	0.15%	0.27%
'Faurecia S.A.'	0.02%	0.11%	0.21%
'Exor S.p.A.'	0.05%	0.26%	0.27%
'Daimler AG'	0.96%	0.08%	0.20%
'Compagnie Generale DES Etablissements Michelin SCA'	0.21%	0.05%	0.07%
'Bayerische Motoren Werke Aktiengesellschaft'	0.37%	0.04%	0.15%
Sum of Weights of other Auto Stocks excluding Volkswagen AG	2.43%	1.32%	2.04%
Active Weights	-	-1.11%	-0.39%
Impact of Returns because of Volkswagen Scandal (18-Sept-2015 to 25-Sept-2015)			
Cumulative Returns	-3.29%	-2.79%	-3.39%
Cumulative Excess Returns	-	0.50%	-0.10%
Weighted Cumulative Returns of Auto Stocks	-0.26%	-0.12%	-0.24%
Weighted Cumulative Excess Returns of Auto Stocks	-	0.14%	0.02%
Percentage of Outperformance because of Underweighted Auto Stocks	-	28.18%	-

PANEL C – Volkswagen AG's weight in constituent Factor-Tilted Indexes

Auto Stocks	Diversified Multi Strategy				Score Weighting			
Weights as of Rebalancing Date 18-Sept-2015	Mid Cap	High Mom	Low Vol.	Value	Mid Cap	High Mom	Low Vol.	Value
'Volkswagen AG'	-	-	-	0.20%	-	--	0.46%	

score-weighted and diversified multi-strategy indexes. The cap-weighted index, being the most concentrated index, attributes 0.71% to Volkswagen AG and 4.62% to other automobile stocks, with a total of 5.34% to the automobile sector as a whole. The score weighted Value strategy, on the other hand, attributes 0.46% to Volkswagen AG and 3.24% to other automobile stocks, with a total of 3.70% to the automobile sector as a whole. The SciBeta Value Diversified Multi-Strategy index, which is a well-diversified index, attributes 0.20% to Volkswagen AG and 2.34% to other automobile stocks, with a total of 2.54% to the automobile sector as a whole. Ultimately, as far as the idiosyncratic risk of VW is concerned, the Diversified Multi-Strategy Value index underweights Volkswagen AG by 0.51% and the score-weighted Value index underweights Volkswagen AG by 0.25% with respect to the SciBeta Cap Weighted Value index. There is therefore a reduction of more than 50% in the Volkswagen AG risk for a well-diversified index compared to a factor index that seeks the maximum Value exposure. This reduction in specific risks is important for the performance of factor indexes. As can be seen, the multi-strategy index outperforms the cap-weighted index by 27 bps overall but the score-weighted index underperforms the cap-weighted index by 59 bps in the week following the scandal.

For many years, the promoters of Value factor indexes have been explaining that the performances of their indexes have been poor because it was not the right time for Value. We feel that this explanation is a bit limited, because while it is true that the Value risk premium has not been the highest over the past five years, it has to be noted that well-diversified Value indexes like Scientific Beta Developed Value Multi-Strategy have outperformed MSCI World over the whole live period, unlike other Value factor indexes, or indexes sold as Value. Exhibit 4 shows that Scientific Beta Developed Value Multi-Strategy is the only Value index that has a better Sharpe ratio than MSCI World over the whole live period (0.89 versus 0.80), with an annual excess return of 0.67%.

Conclusion

In the past few years, many managers and investors have considered that one merely had to invest in factors to be smart. This principle of supporting the existence of risk factors that are better rewarded over the long term than others, which is backed up by extensive academic research, should not make us forget that over the short and medium-term, seeking strong exposure to these factors by concentrating the portfolio can lead to the creation of poorly-diversified factor indexes, and as such can suffer from the existence of a high level of unrewarded idiosyncratic or specific risks.

It is on the basis of this observation that EDHEC Risk Institute and ERI Scientific Beta have always considered that factor investing should be carried out on the basis of a less concentrated index that might be less exposed to a given factor, but is nonetheless better diversified.

In the long term, this approach leads to better Sharpe ratios than what one can obtain from concentrated or score-weighted indexes.

In the short and medium term, it also allows the investor, whatever factor choices have been made, to be sure to benefit from a well-diversified benchmark that is therefore conducive to resisting market events that cannot be avoided through simple multi-factor allocation. •

EXHIBIT 2

Impact of Volkswagen Scandal on Stoxx Europe 600 vs SciBeta Extended Europe Multi-Beta Multi-Strategy EW Index, the MSCI Europe DMFI Index and the JP Morgan Europe Multi-Factor Index.

Analysis is based on weekly total returns in USD from 31-AUG-2015 to 30-SEPT-2015 on Extended Europe Universe. Auto and Auto Parts sector stocks are obtained as per Thomson Reuters Business Classification codes. The SciBeta Extended Europe Multi-Beta Multi-Strategy EW index is the equal-weighted combination of the four factor-tilted multi-strategy indexes – Mid Cap, High Momentum, Low Volatility and Value. Each factor-tilted multi-strategy index selects 50% of stocks from the universe based on the factor score. The multi-strategy weighting scheme is the equal-weighted combination of 5 weighting schemes: Maximum Deconcentration, Maximum Decorrelation, Efficient Minimum Volatility, Efficient Maximum Sharpe Ratio and Diversified Risk Weighted. Each factor-tilted score-weighted index selects 50% of stocks from the universe based on the factor score.

PANEL A – Volkswagen AG

08/31/2015 - 09/30/2015	Performance and Weight Analysis			
	Stoxx Europe 600	SciBeta Extended Europe Multi-Beta Multi-Strategy EW	MSCI Europe DMFI	JP Morgan Europe Multi-Factor
Volkswagen AG Weights as of 31/08/2015	0.35%	0.05%	0.80%	0.49%
Active weights		-0.30%	0.45%	0.14
Cumulative Returns	-4.41%	-2.94%	-3.82%	-4.88%
Attributable to Volkswagen AG	-0.15%	-0.02%	-0.34%	-0.21%
Cumulative Excess Returns	-	1.47%	0.59%	-0.47%
Attributable to Volkswagen AG		0.13%	-0.19%	-0.06%

PANEL B - Other Automobile and Auto Parts Stocks

08/31/2015 - 09/30/2015	Return impact of Automobile Sector ex VW			
	Stoxx Europe 600	SciBeta Extended Europe Multi-Beta Multi-Strategy EW	MSCI Europe DMFI	JP Morgan Europe Multi-Factor
Cumulative Return	-4.41%	-2.94%	-3.82%	-4.88%
Attributable to Auto sector excluding VW	-0.25%	-0.10%	-0.47%	-0.41%
Cumulative Excess Returns	-	1.47%	0.59%	-0.47%
Attributable to Auto sector excluding VW	-	0.14%	-0.22%	-0.16%

EXHIBIT3

Impact of Volkswagen Scandal on SciBeta Value Cap Weighted index vs Value Diversified Multi Strategy index and Value Score-Weighted strategy.

Analysis is based on weekly total returns in USD from 18-Sept-2015 to 25-Sept-2015 on the Extended Europe Universe. Auto and Auto Parts sector stocks are obtained as per Thomson Reuters Business Classification codes. Each factor-tilted score-weighted index selects 50% of stocks from the universe based on the factor score.

PANEL A - Volkswagen AG

Auto Stocks	SciBeta Cap-Weighted	SciBeta Diversified Multi-Strategy	
Weights as of Rebalancing Date 18-Sept-2015	Value	Value	Value
'Volkswagen AG'	0.71%	0.20%	0.46%
Active Weights		-0.51%	-0.25%
Cumulative Returns	-4.14%	-3.87%	-4.73%
Cumulative Excess Returns w.r.t Value Tilted Cap Weighted Index	-	0.27%	-0.59%
Weighted Cumulative Returns of Volkswagen AG	-0.25%	-0.07%	-0.16%
Weighted Cumulative Excess Returns of Volkswagen AG w.r.t Value Tilted Cap Weighted Index	-	0.18%	0.09%

EXHIBIT3 (con't)

PANEL B - Other Automobile and Auto Parts Stocks

Auto Stocks Weights as of Rebalancing Date 18-Sept-2015	SciBeta Cap-Weighted Value	SciBeta Diversified Multi-Strategy Value	Score-Weighted Value
'Valeo SA'	-	-	-
'Renault Société Anonyme'	0.41%	0.14%	0.46%
'Porsche Automobil Holding SE'	0.26%	0.15%	0.49%
'Pirelli & C. SpA'	0.14%	0.40%	-
'Peugeot S.A.'	0.19%	0.44%	0.37%
'Nokian Renkaat Oyj'	-	-	-
'Fiat Chrysler Automobiles N.V.'	0.31%	0.33%	0.39%
'Faurecia S.A.'	-	-	0.23%
'Exor S.p.A.'	0.11%	0.33%	0.40%
'Daimler AG'	2.01%	0.17%	0.29%
'Compagnie Generale DES Etablissements Michelin SCA'	0.45%	0.21%	0.28%
'Bayerische Motoren Werke Aktiengesellschaft'	0.74%	0.16%	0.33%
Sum of Weights of other Auto Stocks excluding Volkswagen AG	4.62%	2.34%	3.24%
Active Weights		-2.28%	-1.38%
Cumulative Returns	-4.14%	-3.87%	-4.73%
Cumulative Excess Returns w.r.t Value Tilted Cap Weighted Index	-	0.27%	-0.59%
Weighted Average Returns of Auto Stocks	-0.53%	-0.26%	-0.46%
Weighted Average Excess Returns of Auto Stocks w.r.t Value Tilted Cap Weighted Index	-	0.27%	0.06%

EXHIBIT 4

Live Performance Comparison of SciBeta Value Diversified Multi Strategy Index vs Competitors.
The analysis is based on weekly total returns in USD from 21-Dec-2012 which is the live date of the SciBeta Developed Value Diversified Multi-Strategy Index to 30-Sep-2015. Yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. MSCI World Index is used as the benchmark. The full names of the external indexes are FTSE Developed Value Factor Index TR, MSCI World Enhanced Value Gross Total Return Index, MSCI World Value Weighted Gross Total Return Index, S&P Enhanced Value Developed Large MidCap Index, FTSE RAFI Developed 1000 Total Return Index and Russell Global Value Total Return Index.

Developed World (21-Dec-2012 to 30-Sep-2015)	MSCI World	SciBeta Developed Value Diversified Multi-Strategy	FTSE Developed Value	MSCI World Enhanced Value	MSCI World Value Weighted	S&P Enhanced Value Developed Large Mid-Cap	FTSE RAFI Developed	Russell Global Value
Annualized Returns	8.86%	9.53%	7.42%	9.49%	7.42%	6.67%	7.58%	6.42%
Volatility	11.09%	10.71%	11.48%	12.26%	11.65%	12.50%	11.58%	11.14%
Sharpe Ratio	0.80	0.89	0.64	0.77	0.63	0.53	0.65	0.57
Relative Returns	-	0.67%	-1.44%	0.63%	-1.44%	-2.19%	-1.28%	-2.44%
Tracking Error	-	1.93%	2.08%	3.38%	1.58%	4.27%	1.76%	1.73%
Information Ratio	-	0.35	-0.69	0.19	-0.91	-0.51	-0.73	-1.41

EXHIBIT 5

Sharpe ratios for concentrated and diversified factor indexes.
The analysis is based on daily total return data from 31/12/1974 to 31/12/2014 (40 years). Mid Cap, High Momentum, Low Volatility, Value, Low Investment and High Profitability selections represent 50%/20% of stocks with such characteristics in a US universe of 500 stocks. Yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. Diversified Multi-Strategy is an equal weighted combination of five different weighting schemes: Maximum Deconcentration, Maximum Decorrelation, Maximum Sharpe Ratio, Minimum Volatility and Diversified Risk-Weighted. S-score for the relevant factor is calculated from the Z-score, which is winsorized at 3 and -3 (i.e., > 3 is set equal to 3 and < -3 is set equal to -3) and is given by: S-score = 1+z [for z>0] and 1/(1-z) [for z<0]. Source: www.scientificbeta.com.

Sharpe Ratio (Dec 1974 – Dec 2014)	50% Stock Selection			20% Stock Selection	
	Diversified Multi-Strategy	Cap Weighting	Score Weighting	Cap Weighting	Score Weighting
Mid Cap	0.70	0.63	0.64	0.62	0.62
High Momentum	0.65	0.48	0.62	0.50	0.57
Low Volatility	0.70	0.49	0.69	0.57	0.74
Value	0.71	0.53	0.70	0.56	0.75
Low Investment	0.71	0.55	0.64	0.70	0.61
High Profitability	0.65	0.45	0.66	0.51	0.69
Average across 6 Factors	0.69	0.52	0.66	0.58	0.66

INDEXES

Skewness: A New Signal for Long-Short Commodity Investing

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Recent theories are moving away from the basic notion that investors make investment decisions purely on the basis of expected return and risk, and suggest that the expected skewness of an asset's returns (i.e. the extent to which the distribution of returns is more tilted towards gains or losses) also influences their investment decisions. Several empirical studies confirm this new paradigm (see e.g. Kumar, 2009) by showing that investors have preferences for assets whose returns are positively skewed and shy away from assets whose returns are negatively skewed. This preference for positively skewed assets and aversion towards negatively skewed assets implies that positively skewed assets become overpriced, while negatively skewed assets become underpriced. While this pattern is well documented in the equity market literature (see, for example, Amaya et al., 2015, for some recent evidence), the question as to whether skewness strategies are profitable in alternative assets, such as commodity futures, is still to be addressed. We fill this gap by providing an empirical investigation of the profitability of skewness trading in commodity futures markets.[19]

Developing a trading strategy in commodity futures

We first focus our attention on the design of a trading strategy that is built on the extent of past skewness observed in commodity futures.[20] Exploiting a wide cross-section of 27 commodity futures,[21] we measure the skewness of each commodity future's returns over a ranking period of 12 months with observations sampled at the daily frequency. The skewness strategy takes a long position in the 20% of contracts with the most negative skewness and a short position in the 20% of contracts with the most positive skewness; the long and short positions (with equally-weighted constituents) are held on a fully-collateralized basis for one month.

We proceed likewise to construct long-short portfolios based on the slope of the term structure of commodity futures prices, past performance and hedging pressure. The motivation for choosing these portfolios as benchmarks against which to appraise performance stems from the literature on backwardation and contango which suggests that these portfolios are key to explaining the pricing of commodity futures (Basu and Miffre, 2013; Szymanowska et al., 2014; Bakshi et al., 2013). More specifically, the term structure strategy is long the quintile of commodities with the most downward-sloping term structures (or highest roll-yields) and is short the quintile of commodities with the most upward-sloping term structures (or lowest roll-yields). The momentum portfolio is long the quintile of commodities with the best past performance and is short the quintile of commodities with the worst past performance. The hedging pressure portfolio is long the quintile of assets for which speculators' open interest is the longest and hedgers' open interest the shortest, and is short the quintile of assets for which speculators are the shortest and hedgers the longest.

To appraise the performance of the newly designed skewness strategy we also use as a benchmark two long-only portfolios (the S&P-GSCI and a long-only equally-weighted

> A trading strategy that systematically buys commodities with low skewness and sells commodities with high skewness is highly profitable.

EXHIBIT 1

Summary Statistics of Performance.
The table presents summary statistics for long-only, short-only and long-short commodity portfolios. Sharpe ratios (SR) are annualized mean excess returns (Mean) divided by annualized standard deviations (StDev). Alpha measures the abnormal performance of the long-only, short-only and long-short skewness strategy relative to a four-factor model that includes TS, Mom, HP and EW. Conventional significance t-ratios are reported in parentheses. The sample spans January 1987 to November 2014.

	Mean		StDev	SR	α	
Panel A: Skewness portfolio						
Long (most negative skew)	0.0512	(1.52)	0.1748	0.2932	0.0428	(1.79)
Short (most positive skew)	-0.1089	(-3.54)	0.1596	-0.6820	-0.0889	(-3.96)
Long-short	0.0801	(4.08)	0.1020	0.7848	0.0658	(3.58)
Panel B: Alternative strategies						
Term structure (TS)	0.0463	(2.05)	0.1196	0.3873		
Momentum (Mom)	0.0895	(3.25)	0.1455	0.6153		
Hedging pressure (HP)	0.0578	(2.53)	0.1206	0.4796		
Equally-weighted long-only portfolio (EW)	-0.0021	(-0.09)	0.1207	-0.0175		
S&P-GSCI	0.0034	(0.09)	0.1989	0.0169		

[19] *The reader interested in the technical details may find them in Fernandez-Perez et al. (2015).*

[20] *Skewness is defined as* $Sk = \left[\frac{1}{D}\sum_{d=1}^{D}(r_d - \mu)^3\right] / \sigma^3$ *where* r_d *is the daily return of a given commodity on day* d, μ *and* σ *are the mean and standard deviation of daily returns, respectively, and* D *is the number of daily observations with a period of 12 months.*

[21] *We use 12 agricultural commodities (cocoa, coffee C, corn, cotton n°2, frozen concentrated orange juice, oats, rough rice, soybean meal, soybean oil, soybeans, sugar n° 11, wheat), 5 energy commodities (electricity, gasoline, heating oil n° 2, light sweet crude oil, natural gas), 4 livestock commodities (feeder cattle, frozen pork bellies, lean hogs, live cattle), 5 metal commodities (copper, gold, palladium, platinum, silver), and random length lumber. Series of continuous futures returns are constructed under the assumption that agents hold the nearest-to-maturity contract up to one month before maturity and then roll to the then-nearest contract. The dataset covers the sample period spanning January 1987 - November 2014*

monthly-rebalanced portfolio of all commodity futures), thereby naively assuming that commodity futures markets are solely backwardated.

Performance is presented in Exhibit 1. In line with research from the equity market, commodity futures with the most negative skew in the ranking period tend to surprise us positively, earning 5.12% a year. As anticipated, commodities with the highest level of skewness underperform, losing 10.89% a year. Systematically buying the most negatively skewed commodities and shorting the most positively skewed commodities yields a positive and statistically significant mean excess return of 8.01% a year with a t-statistic of 4.08 (Panel A). With a Sharpe ratio of 0.78, the performance of the long-short skewness portfolio compares very favorably to that obtained with traditional long-only and long-short portfolios (Panel B). The latter indeed generate Sharpe ratios that merely range from -0.02 for the equally-weighted long-only portfolio to 0.62 for the long-short momentum portfolio. As previously documented, the long-short portfolios perform better than the long-only ones, highlighting the importance of accounting for both backwardation and contango when pricing commodity futures.

Exhibit 2 plots the time evolution of $1 invested at the beginning of the sample period in the four long-short strategies, as well as in the two long-only portfolios. The long-short skewness portfolio clearly stands out: it seems to offer good performance and low volatility.

Exhibit 1 also indicates that the long-short skewness strategy yields significant abnormal performance (alpha of 6.58% a year with a t-statistic of 3.58) relative to a commodity pricing model that utilizes as risk factors the excess returns of a long-only equally-weighted portfolio of all commodities, alongside the excess returns of term structure, momentum and hedging pressure portfolios. This shows that skewness is not merely an artifact of previously documented relationships between commodity futures returns and commodity risk factors. To put this differently, the skewness signal captures risks beyond those embedded in the backwardation and contango phases known to be present in commodity futures markets. Skewness risk may uniquely relate to the preferences of investors for lottery-like commodity futures payoffs.

Robustness analysis

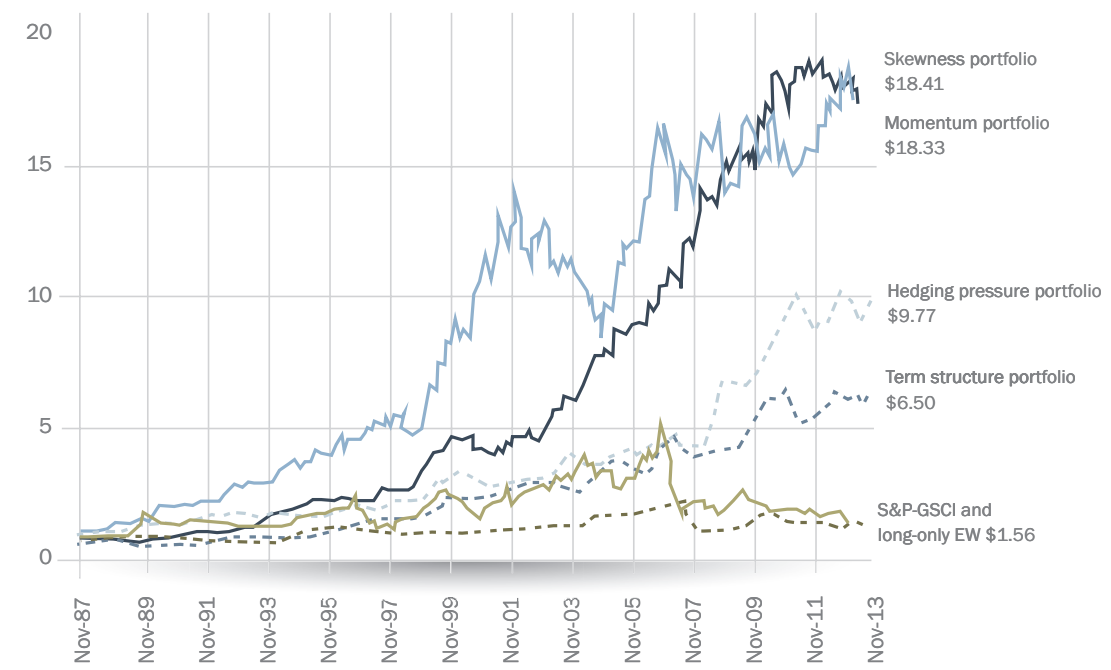
Exhibit 3 examines the robustness of the performance of the low-minus-high skewness portfolio to various specifications of the methodology employed (Panels A and B), the cross-section of commodities considered (Panel C), liquidity and transaction costs considerations (Panel D) and the sample periods analyzed (Panel E).

Exhibit 3, Panels A and B test the robustness of the performance of the low-minus-high skewness portfolio to the ranking period employed to measure the skewness of each asset (Panel A) and to the holding period of the long-short portfolios (Panel B). Irrespective of the ranking and holding periods considered, the long-short portfolios are shown to perform well, suggesting that the negative relationship between skewness and returns previously identified is robust to these settings.

It might be intuitive to think that seasonals in supply and demand could induce extreme levels of skewness and subsequent mean reversion. For example, in periods of stock-outs or more generally before harvest, commodity futures prices may rise, inducing positive skewness; the same futures prices will eventually mean revert as inventories are replenished and markets shift into contango; namely, during and right after the next harvest. To assess whether seasonals in supply and demand drive the results obtained thus far, we split our cross-section of 27 commodities into seasonals and non-seasonals, where the first group includes the 21 agricultural, livestock and energy commodities and the second group includes the five metals alongside random length lumber. The results reported in Panel C show that skewness matters for both seasonal and non-seasonal commodities, with negatively skewed commodities outperforming positively skewed commodities. To further test whether seasonalities in commodity prices drives the observed profitability, we also remove seasonality out of commodity future returns through monthly dummies and then obtain the skewness of the de-seasonalized returns. Reassuringly, Panel C shows that the low-minus-high de-seasonalized skewness portfolio generates positive and significant performance. We conclude therefore that the results are robust to the cross-section of commodities considered and are not driven by seasonality in supply and demand.

EXHIBIT 2

Future Value of $1 Invested in Long-Only and Long-Short Commodity Portfolios.



As a further robustness check, we address possible concerns over lack of liquidity by examining the performance of the strategies when we exclude the 10% of commodities with the lowest average open interest over the 12 months preceding portfolio formation. The results reported in the first row of Exhibit 3, Panel D demonstrate that the low-minus-high skewness strategy still works well when illiquid assets are excluded and thus that the performance reported in Exhibit 1 is not merely a compensation for illiquidity. Panel D also tests the impact that transaction costs may have on the profitability of the strategy. Relative to Locke and Venkatesh (1997), we are conservative in setting transaction costs at 0.033% and at twice that amount (0.066%) per trade; the results indicate that the skewness strategy is cheap to implement and profitable net of transaction costs. Finally, the last row of Panel D presents the level of transaction costs per trade that would make the skewness strategy break-even. That level is estimated at 0.933% per round-trip transaction, an estimate that by far exceeds the conservative measure of transaction costs proposed by Locke and Venkatesh (1997). Taken altogether, the evidence presented in Exhibit 3, Panel D indicates that the performance of the low-minus-high skewness portfolio is not merely an illiquidity premium or a reward for transaction costs.

Finally, Exhibit 3, Panel E summarizes the performance of the long-short skewness strategies over i) two sub-periods of roughly equal length (January 1987-May 2001 and June 2001-November 2014), ii) two sub-periods, respectively, preceding and following the financialization of commodity futures markets dated January 2006 as suggested, and iii) two sub-periods, respectively, preceding and reflecting the financial crisis of the late 2000s, using July 2007 as an approximate date. The results are found to be more or less robust: the performance of P1-P5 does not seem to be sample-specific.

Conclusions

In this article, we show that a trading strategy that systematically buys commodities with low skewness and sells commodities with high skewness is highly profitable. The returns to this strategy do not seem to be merely a compensation for the risks present in commodity futures markets, for the transaction costs incurred in implementing the trades or for the relative lack of liquidity of the assets traded. Finally we show that the conclusion holds for various sub-samples, for different subsets of commodities (seasonal and non-seasonal), and for the large majority of the ranking and holding periods considered. •

EXHIBIT 3

Robustness Analysis.
This table tests the robustness of the performance of the low-minus-high skewness portfolio to various methodological specifications (Panels A and B), the presence of seasonality in supply and demand (Panel C), liquidity and transaction cost considerations (Panel D) and the samples analyzed (Panel E). Mean is the annualized mean excess returns of the long/short skewness portfolio, StDev is the annualized standard deviation of its returns, SR stands for the Sharpe ratio, is the annualized abnormal performance of the low-minus-high skewness portfolio, measured as the intercept from a regression of the portfolio excess returns onto a four-factor model that includes the long/short portfolios based on term structure, momentum and hedging pressure signals, and a long-only equally-weighted portfolio of all commodities. R is the ranking period over which the skewness signal is measured, H is the holding period of the long/short skewness portfolio (both expressed in months). Newey-West t-statistics for the alphas are reported in parentheses. Unless specified otherwise, R=12, H=1 and the sample covers the period January 1987 – November 2014.

	Mean		StDev	SR	α	
Panel A: Choice of ranking periods (R=12)						
R=6	0.0556	(2.94)	0.0991	0.5615	0.0479	(2.57)
R=12	0.0801	(4.08)	0.1020	0.7848	0.0658	(3.58)
R=36	0.0516	(2.48)	0.1041	0.4959	0.0388	(1.66)
R=60	0.0591	(2.46)	0.1149	0.5140	0.0474	(2.00)
R=96	0.0649	(2.52)	0.1153	0.5632	0.0533	(1.93)
Average	0.0623		0.1071	0.5839	0.0506	
Panel B: Choice of ranking periods (H=1)						
R=12	0.0801	(4.08)	0.1020	0.7848	0.0658	(3.58)
H=3	0.0828	(4.21)	0.1022	0.8100	0.0618	
H=6	0.0616	(3.13)	0.1023	0.6022	0.0424	
H=12	0.0514	(2.63)	0.1015	0.5065	0.0278	
Average	0.069	0.1020	0.6759	0.0495		
Panel C: Seasonality in supply and demand						
Seasonal commodities	0.0862	(3.89)	0.1150	0.7492	0.0713	(3.60)
Non-seasonal commodities	0.0616	(2.07)	0.1549	0.3979	0.0540	
De-seasonized skewness portfolio	0.0709	(3.56)	0.1036	0.6842	0.0518	
Panel D: Lack of liquidity and transaction costs						
90% most liquid contracts	0.0631	(3.30)	0.0992	0.6364	0.0504	(2.61)
T-costs = 0.033%	0.0783	(3.99)	0.102	0.768	0.0641	(3.49)
T-costs = 0.066%	0.0766	(3.90)	0.102	0.7512	0.0624	(3.40)
Break-even T-costs	0.933					
Panel E: Sub-sample analysis						
Jan 1987-May 2001	0.0705	(2.51)	0.1032	0.6837	0.0534	(2.02)
June 2001-Nov 2014	0.0896	(3.26)	0.1010	0.8864	0.0683	(2.63)
Jan 1987-Dec 2005	0.0774	(3.10)	0.1062	0.7289	0.0712	(2.89)
Jan 2006-Nov 2014	0.0855	(2.73)	0.0935	0.9145	0.0372	(1.94)
Jan 1987-July 2007	0.0767	(3.25)	0.1047	0.7329	0.0698	(3.00)
Aug 2007-Nov 2014	0.0890	(2.54)	0.0950	0.9370	0.0290	(1.33)

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