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P&I CONTENT SOLUTIONS GROUP

Research for Institutional Money Management

EDHEC BUSINESS SCHOOL

INTRODUCTION

Introduction to Research for Institutional Money Management supplement in P&I

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

We first look at the use of academically grounded factors in investment practice. We observe that the factor finding process often maximizes the risk of finding false factors, so most factors used in commercially available tools and products are likely to be false. We conclude that the use of non-standard factors can lead to unintended exposures and misunderstandings concerning the risk exposures.

Scientific Beta's defensive offering relies on three different indexes to satisfy investors' various objectives and constraints. In line with the defensive objective, they deliver good levels of volatility reduction and capital protection in bear markets relative to the cap-weighted index.

We examine changes that are made to indexes. Methodologies of factor-based equity indexes undergo frequent changes, leading to inconsistencies over time. Inconsistencies in index methodology make it difficult for investors to evaluate index offerings and may expose them to a risk of relying on spurious performance records.

We propose to apply the principles of goal-based investing to the design of a new generation of "flexicure" retirement investment strategies, which aim at offering the best-of-both-worlds between insurance products and asset management products. These strategies can be used to help individuals and households secure minimum levels of replacement income while generating upside exposure through liquid and reversible investment products.

In research that is drawn from the Amundi "ETF, Indexing and Smart Beta Investment Strategies" research chair at EDHEC-Risk Institute, we propose a detailed empirical study of implementable unconditional and conditional carry strategies in the US Treasury market. The aim is to assess whether the level factor remains conditionally and unconditionally rewarded when strategies are implemented using actually traded bonds rather than "virtual" discount bonds.

In new research from the EDHEC Infrastructure Institute (EDHECinfra), supported by the Long-Term Infrastructure Investors' Association (LTIIA) as part of the EDHEC/LTIIA research chair on Infrastructure Equity Benchmarking, we show that systematic risk factors can largely explain the evolution of average prices but also that valuations have shifted to a higher level. We show that unlisted infrastructure equity prices do not exist in a vacuum but are driven by factors that can be found across asset classes.

Additional research from EDHECinfra, supported by Natixis as part of the EDHEC/Natixis research chair on Infrastructure Debt Benchmarking, examines the drivers and evolution of credit spreads in private infrastructure debt. We show that common risk factors partly explain both infrastructure and corporate debt spreads. However, the pricing of these factors differs, sometimes considerably, between the two types of private debt instruments.

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

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Using Academically Grounded Factors in Investment Practice

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- **Common investment practices do not employ academically grounded factor definitions**
- **The factor finding process often maximizes the risk of finding false factors.**
- **Thus most factors used in commercially available tools and products are likely false.**
- **The use of non-standard factors can lead to unintended exposures and misunderstandings concerning the risk exposures.**

The Promise of Factor Investing

Factor investing offers a big promise. By identifying the persistent drivers of long-term returns in their portfolios, investors can understand which risks they are exposed to, and make explicit choices about these exposures. This idea has gained popularity among long-term investors ever since the publication in 2009 of an influential report by finance professors on the performance of the Norwegian sovereign fund (Ang et al., 2009).

An often-cited analogy is to see factors as the "nutrients" of investing. Just like information on the nutrients in food products is relevant to consumers, information on the factor exposures of investment products is relevant to investors. This analogy also suggests that factors cannot be arbitrary constructs. What would you think if Nestlé used its own definition of "saturated fat" for the information on its chocolate packets and if McDonald's also had its own, but different, definition for the content of its burgers? Further, would it not be curious if both definitions had nothing to do with the definition that nutritionists and medical researchers use?

When it comes to information about factors, however, this is exactly the situation that we find. Investment products that aim to capture factor premia have gained popularity. Furthermore, investors rely heavily on analytic toolkits to identify factor exposures of an investor's portfolio. However, neither investment products nor analytic tools necessarily follow the standard factor definitions that peer-reviewed research in financial economics has established.

Investors benefit from understanding and controlling their exposure to factors, only if these factors are reliable drivers of long-term returns. Factor definitions that have survived the scrutiny of hundreds of empirical studies and have been independently replicated in a large number of data sets are of course more reliable than ad-hoc constructs used for the specific purposes of a product provider.

Perhaps more importantly, the process by which factors are defined in practice is inherently flawed. Common practices in designing these factors increase the risk of retaining factors that will ultimately be irrelevant as drivers of long-term returns.

This article will discuss factor definitions used in investment products and analytic tools offered to investors and contrast them with the standard academic factors. We also outline why the methodologies used in practice pose a high risk of ending up with irrelevant factors.

Are Factors Grounded in Academic Research?

Factor models link returns of any investment strategy to a set of common factors. In addition to the market factor, commonly used factors include size, value, momentum, profitability and investment, which capture the difference of returns across firms with different characteristics. In financial economic research, a small number of models have become workhorses for analyzing asset returns and fund manager performance, given the consensual understanding that they contain the factors that matter for asset returns. Providers of factor-based investment tools and strategies unequivocally claim that their factors are "grounded in academic research"[1]. However, we will show that the factors used are instead completely inconsistent with the factors that are supported by a broad academic consensus.

5 or 500 factors?

Exhibit 1 provides an overview of the workhorse models in academic finance. There are three obvious insights:

- Different models use identical factor definitions;
- The number of factors is limited to about a handful of factors;
- Factors are defined by a single variable.

These three properties ultimately mean that the different factor models draw on very few variables, which have been identified as persistent drivers of long-term returns.

In contrast, the factor tools from commercial providers typically include a proliferation of variables. MSCI's "Factor Box" draws on 41 different variables to capture the factor exposures of a given portfolio[2]. S&P markets a "Factor Library" which, despite including more than 500 variables[3] "encompassing millions of backtests," wants to help you "simplify your factor investing process". BlackRock proudly announces "thousands of factors" for its Aladdin Risk tool.[4]

This raises the question of why the standard models avoid such a proliferation of variables. First, the need for more factors is often rejected on empirical grounds. For example, Hanna and Ready (2005) show that using 71 factors does not add value over a model with two simple factors (book-to-market and momentum). Similarly, Hou, Xue and Zhang (2015) show that a model with four simple factors does a good job at capturing the returns across a set of nearly 80 factors. Second, academic research limits the number and complexity of factors because a parsimonious description of the return patterns is likely to be more robust. Increasing the number of variables will obviously improve fitting the model to a given data set but will also reduce the robustness when applying model results beyond the dataset of the initial tests. These two points are analyzed in more detail later in the paper.

Non-Rewarded versus Rewarded Factors

Before we proceed, it is necessary to clarify a common source of confusion. Several definitions of the term "factors" exist, with some of them focused on the variability in returns (i.e. short term fluctuations) and others on the expected returns of assets (i.e. long term average returns). Martellini and Milhau (2018) provide a taxonomy of factors that distinguishes between these different definitions and their uses. A first type of factors can be used to describe common sources of risk across assets. In this setting, volatilities and correlations among the assets are driven by exposures to a certain set of factors. While this information can provide some understanding of the fluctuations in a portfolio, it does not explain what the driver of long-term returns is. Such factors are referred to as non-rewarded factors. Naturally, there are a number of such non-rewarded factors that can help capture short-term fluctuations. For example, short-term fluctuations of an equity portfolio may be explained by its sector exposures, its country exposures, exposures to currency or commodity risks, among many other possibilities. However, since such factors are not rewarded, an investor does not gain additional returns from such exposures.

Rewarded factors are factors that explain differences in the long-term expected return in the cross-section of the assets. From an allocation point of view, knowledge about these factors enables an investor to tilt a portfolio towards stocks with high exposure to a factor that is positively rewarded. This results in a higher long-term expected return for the portfolio. Investors need to be cautious to avoid misinterpreting a factor offered in commercial factor tools as rewarded, when it is actually not. Dividend yield, for example, is included in the factor model of MSCI because it is a source of "time-varying return and risk"[5]. However, it does not explain cross-sectional differences in the long-term expected return (Hou et al., 2015).

Exhibit 2 provides an illustration to explain this distinction further. Suppose an investor in an equal-weighted equity index wants to understand the implicit sector bets he makes. For this purpose, he is interested in the portfolio's exposure to an industry factor that is proxied by the performance difference between technology and

[1] See "Foundations of Factor Investing", MSCI Research Insight (December 2013).
[2] See MSCI (2017): "Use of the Global Equity Model (GEM LT) In MSCI Index Construction" , available at <https://bit.ly/2x2EhOx>
[3] See <https://bit.ly/2OdlhTS>
[4] See <https://bit.ly/2x8D8Vz>
[5] See "Best practices in factor research and factor models" MSCI Research Insight (November 2018), available at <https://www.msci.com/www/research-paper/best-practices-in-factor/01163021280>

EXHIBIT 1

Factor Definitions in Equity Factor Models that are Predominant in the Academic Literature on Mutual Fund Performance Evaluation and Asset Pricing

	Factor Definitions for					Number	
	Size	Value	Momentum	Profitability	Investment	of non-market factors	of variables per factor
Fama, French (1993)	Market	Book/				2	1
Carhart (1997)	Cap	Market	Past			3	1
Chordia, Goyal, Saretto (2017)			Returns	Gross Profit	Asset	5	1
Fama, French (2015)				Book Equity	Growth	4	1
Hou, Xue, Zhang (2015)				Profit/Book Equity		3	1

EXHIBIT 2

Risk and Return Influence of the Technology minus Utilities Factor (TMU) on an Equal-Weighted Portfolio

The top row of the table shows the regression results of the excess returns of the equal-weighted portfolio over the risk-free rate on the TMU factor. The bottom row shows the long-term performance of the TMU factor. The analysis is based on daily total returns for the period 19-Jun-1970 to 29-Dec-2017. The stock universe consists of the 500 largest US stocks. The equal-weighted portfolio is represented by the EDHEC-Risk Long-Term United States Maximum Deconcentration Index. The TMU factor returns are calculated as the returns on the cap-weighted portfolio of the technology stocks in the universe minus the returns on the cap-weighted portfolio of the utility stocks in the universe. The secondary market US Treasury Bills (3M) is the risk-free rate.

Regression results	Coefficient	P-value	R^2
Explaining short term fluctuations	0.32	0.00	0.19
Long-term returns	**Ann. Return**	**P-value**	
Factor premium (long-term average return)	-0.97%	0.65	

utility stocks. While this analysis can provide information about the way the portfolio return varies with the differences in sector performance, it will not necessarily explain the long-term returns of the portfolio.

The first row of the table shows the results of a regression of the excess returns of the equal-weighted index on the industry factor. The p-value of zero indicates that the exposure is highly significant. The R^2 suggests that the industry factor explains around 20% of the variance in portfolio returns. Therefore, in terms of understanding the short-term variability in returns, this analysis can be useful. The bottom row of the table, however, shows that the factor does not exhibit a long-term return that is significantly different from 0. Exposure to this factor will thus not be useful to understand the long-term return drivers of the portfolio. Furthermore, tilting the portfolio towards stocks with a high exposure to this factor will not result in a higher expected return. The idea of factor investing is to tilt a portfolio towards a rewarded risk factor. Without a long-term premium, there would be no reason to take on the factor's risk.

Spurious Factors

A severe problem with commercially used factors is the process by which they are defined. This process increases the risk of falsely identifying factors, due to weaknesses in the statistical analysis. In fact, providers will analyze a large set of candidate variables to define their factors. Given today's computing power and the large number of variables representing different firm characteristics, such an exercise makes it easy to find so-called "factors" that work in the given dataset. However, these factors most likely will have no actual relevance outside the original dataset. That data-mining will lead to the identification of false factors is a problem that is well known to financial economists. Lo and MacKinlay (1990) provided an early warning against careless analysis: "[…] the more scrutiny a collection of data is subjected to, the more likely will interesting (spurious) patterns emerge."

Selection Bias

It is well known that simply seeking out factors in the data without a concern for robustness will lead to the discovery of spurious factors. This is due to a "selection bias" of choosing among a multitude of possible variables. Harvey et al. (2016) document a total of 314 factors with positive historical risk premia showing that the discovery of the premium could be a result of data-mining (i.e. strong and statistically-significant factor premia may be a result of many researchers searching through the same dataset to find publishable results). The practice of identifying merely empirical factors is known as "factor fishing" (see Cochrane, 2001). Therefore, a key requirement for investors to accept factors as relevant in their investment process is that there be clear economic rationale as to why the exposure to this factor constitutes a systematic risk that requires a reward, and why it is likely to continue producing a positive risk premium (Kogan and Tian, 2013). In short, factors selected on the sole basis of past performance without considering any theoretical evidence are not robust and must not be expected to deliver similar premia in the future. This is emphasized by Harvey (2017), who argues that "economic plausibility must be part of the inference".

In addition, there are statistical tools to adjust results for the biases arising from testing a large number of variables. A recent study Chordia et al. (2017) also emphasizes the factor-fishing problem. They show that it is easy to find great new factors in backtests but such factors add no real value to standard factors. They create more than two million factors (levels, growth rates, and ratios) from 156 accounting variables and assess whether these factors generate performance. While they find that there are 22,337 (!) great factors, the winning ratios do not make any economic sense (such as the ratio of Common Stock minus Retained Earnings to Advertising Expense). Moreover, these factors do not survive more careful vetting. None of the 20,000+ factors that appear significant survives after adjusting for the well-known standard factors (size, value, momentum, profitability, investment and market) and for selection bias. These results emphasize that it is easy to discover new factors in the data if enough fishing is done, but such factors are neither economically meaningful nor statistically robust.

Of course, exposure to non-robust factors with an unreliable backtest performance will not prove useful to an investor going forward. The past will give an inflated picture of the factor-based performance that can be expected for the future.

Composite Scores

In the discussion thus far, we emphasized that a stark problem arises from a practice where providers of factor tools select flexibly from among many variables. It turns out that the actual problem is even worse in practice. Providers of factor products and tools do not stop their data-mining practices at the level of selecting single variables. Instead, they create complex composite factor definitions drawing on combinations of variables.

Research by Novy-Marx (2015) shows that the use of composite variables in the definition of factors yields a "particular pernicious form of data-snooping bias", the overfitting bias. Intuitively, this bias arises because, in addition to screening the data for the best-performing variables, combining variables that give good backtest results provides even more flexibility to seek out spurious patterns in the data. The author concludes that "combining signals that backtest positively can yield impressive back-tested results, even when none of the signals employed to construct the composite signal has real power".

When combining variables to improve back-tested factor performance, providers can yet again increase flexibility for capturing spurious patterns in the data. Additional flexibility is easily achieved by attributing arbitrary weightings to the variables used in a composite definition. For a given combination of variables, changing the weight each variable receives in the factor definition may have a dramatic impact on factor returns. Exhibit 3 illustrates this point. The graph plots return differences over three-year horizons of two factor-tilted portfolios that draw on the same three variables to define a quality score. The only difference between the quality factor definitions is the weighting of the three component variables (profitability, leverage and investment). The difference in weightings used in the composite factor definitions leads to return differences that often exceed 5% annualized. Such pronounced differences suggest that, in a given sample, it is easy to improve factor returns by specifying arbitrary weightings for composite factor definitions.

What Do Providers Do?

Given the well-documented risk of biases leading to useless factors, providers of factor products should use the academically validated factor definitions. Indeed, many providers claim that their factors are grounded in academic research. MSCI, for example, recently issued a report that clearly emphasizes this.[6] They state that their "factor research is firmly grounded in academic theory and empirical practice". FTSE also mentions the broad academic consensus that exists for the factors used in their global factor index series.[7]

It is important to highlight, however, what having a strong academic foundation should mean. To claim that a specific factor is "firmly grounded" in academic research means that it should fulfil two criteria. First, its existence should be replicated and documented across different independent studies. This gives investors the assurance that the methodologies are externally validated and that the factors also exist outside of the original data set. Second, a risk-based explanation should support the existence of the factor. Without this, there is no reason to expect the persistence of the factor performance. Post-publication evidence is needed to confirm that the factor does not disappear after it is published. To support a claim for academically grounded factors, providers should be able to list the independent studies showing that these two requirements are fulfilled.

This does not mean that using new or proprietary factors will necessarily fail out of sample. However, the problem is that it is not possible to obtain the same assurances for the effectiveness of the factor compared to academically grounded factors. Hou et al. (2018) show that the majority of anomalies in financial research cannot be replicated. This means that there is no reason to assume that they will be useful for an investor going forward. A prudent approach is thus to only select factors that have indeed been independently replicated. With this in mind, why would one rely on provider specific research concerning a new factor when you have free due diligence from the academic community concerning a standard set of factors? Consequently, it is clear that the use of proprietary factors exposes an investor to risks that can easily be avoided.

Whereas the factor names are usually based on factors that are presented in the literature, the actual implementation of most product providers is very different. Exhibit 4 gives some examples of variable definitions being used by different index providers as a proxy for the factors. These can be compared to the definitions academics use for the factors, as displayed in Exhibit 1 earlier. It is clear that provider definitions are more complex than academic factor definitions and differ substantially from the externally validated factors despite using the same factor labels, such as "value" and "momentum". A relevant question for investors is whether the "upgraded" definitions of standard factors, like "enhanced value" and "fresh momentum" add value only in the backtest or whether the benefits hold post publication (i.e. in a live setting). Moreover, in the absence of external replication of such factors, investors are fully reliant on provider-specific results.

The exhibit also shows that many providers use composite scores in their factor definitions. As discussed above, this opens the door for an overfitting bias, even if composites are equal-weighted across constituent variables. Providers add even more flexibility to their factor definitions by making decisions on how to weigh the different variables within the composite. For example, one provider uses an approach involving "intuition […], investors' expectations or other measures"[8] to attribute weights when combining variables into composites[9]. Another provider uses a statistical procedure to weight variables making up a composite factor.[10]

Overall, product providers explicitly acknowledge that the guiding principle behind factor definitions is to analyze a large number of possible combinations in short data sets and then retain the factors that deliver the highest backtest performance. In fact, providers' product descriptions often read like a classical description of a data-snooping exercise, which is expected to lead to spurious results. For example, one provider states[11] that, when choosing among factor definitions, "adjustments could stem from examining factor volatilities, t-stats, Information Ratios", with an "emphasis on factor returns and Information Ratios". Another provider states that "factors are selected on the basis of the most significant t-stat values", which corresponds to the technical definition of a procedure that maximizes selection bias[12].

Despite a lack of empirical or economic grounding, factor definitions used by providers may appear to be advantageous in practice. This is the case notably when index providers offer both analytics tools and indexes, and ensure that factor definitions in their indexes correspond to those used in their tools. If an analytics tool and a set of indexes are based on the same factor definitions, the indexes will show an exposure to the factors by construction. Other investment strategies may be more difficult to explain by the proprietary factor definitions of the provider and thus appear more difficult to interpret to investors. However, if the factors are flawed to start with, such correspondence of course does not add any real value to investors.

Redundant Factors

For many factors used in investment practice, it is well known that they fail to deliver a significant premium. For example, different analytics packages[13] include the dividend yield, leverage, and sales growth as factors, while all of these factors have been shown not to deliver a significant premium (for the Dividend Yield, see Hou et al. [2015], for leverage see Kyosev et al. [2016], for growth see Lakonishok et al. [1994]).

Factors may also be redundant with respect to consensual factors from the academic literature. In fact, many proprietary factors may have return effects, which can be explained away by the fact that they have exposures to standard factors (see Fama and French, 1996). We can illustrate this point by analyzing the popular dividend yield factor.

Exhibit 5 shows that the dividend yield factor does not lead to significant returns. Moreover, when adjusting returns for the exposure to the standard value (book-to-market) effect, the dividend yield factor actually delivers negative returns.

Popular factor products and tools contain a large number of factors that do not deliver an independent long-term premium. This is bad news for investors who are using such tools to understand the long-term return drivers of their portfolios.

Getting Your Exposures Wrong

Below, we will illustrate the risks of using non-standard factors. We will look at the results of a set of regressions of the excess returns of two composite quality factor indexes over a broad cap-weighted index[14] on the returns of academically-grounded and widely-accepted factors, including the quality-related factors of profitability and investment. This will allow us to assess the exposures of the quality indexes to the academic factors and show that there is a clear mismatch between the intended and achieved exposures. As the quality factor indexes, we use the MSCI World Quality Index (MQI) and the FTSE Developed Quality Factor Index (FQI). The former "aims to capture the performance of quality growth stocks by iden-

[6] See "Best practices in factor research and factor models" MSCI Research Insight (November 2018), available at <https://www.msci.com/www/research-paper/best-practices-in-factor/01163021280>
[7] See <https://www.ftse.com/products/indices/factor>
[8] See MSCI (2018), Introducing MSCI FaCS, available at <https://www.msci.com/documents/10199/d923cc18-6493-4245-9707-56e9b6609528>
[9] It is further stated in a different publication that "equal weights are used unless there are compelling reasons to deviate from them", see "Best practices in factor research and factor models" MSCI Research Insight (November 2018) available at <https://www.msci.com/www/research-paper/best-practices-in-factor/01163021280>. Of course, if one wanted to limit flexibility it would be necessary to state stronger constraints than a broad reference to requiring "compelling reasons" for deviation.
[10] See Sousa Costa and Marques Mendes (2016), available at: <https://bit.ly/2p1mnbd>
[11] See MSCI (2018), Introducing MSCI FaCS, available at <https://www.msci.com/documents/10199/d923cc18-6493-4245-9707-56e9b6609528>
[12] See FTSE (2014), "Factor exposure indexes - Value factor", available at <https://www.ftserussell.com/sites/default/files/research/factor_exposure_indexes-value_factor_final.pdf>
[13] See for example Style Analytics (2018), available at https://bit.ly/2Nznq04.
[14] We use the MSCI World Index as the broad cap-weighted index.

EXHIBIT 3

Difference Between Annualized 3-Year Rolling Returns of Two "Quality" Portfolios Using Different Weightings on the Same Set of Variables.
The weights in the two portfolios are as follows. Portfolio 1: Inv. 30%, Prof. 60%, Lev. 10%, Portfolio 2: Inv. 60%, Prof. 30%, Lev. 10%. Analysis is based on daily total returns in USD, from 31-Dec-1976 to 31-Dec-2016. The plotted line corresponds to the difference between three-year rolling annualized returns of the two 'Quality' portfolios. Portfolios were formed by selecting stocks with the top 10% composite score and equal weighting them. The composite scores were defined by investment, profitability and leverage scores, weighted in two different ways: 60-30-10 and 30-60-10 respectively. The composite scores are standardized using cap-weighted mean and unit standard deviation.

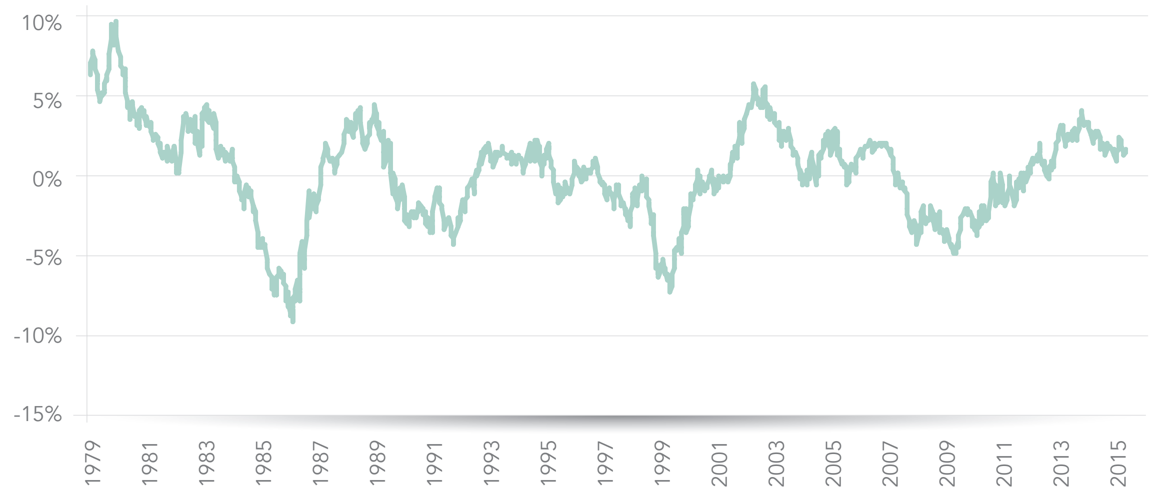

EXHIBIT 4

Examples of variable definitions used by index providers[15]

Factor	FTSE	MSCI	S&P	RAFI
SIZE	Log of full market cap	Equal-weighted	-	Equal weight of small universe portfolios of value, low volatility, quality and momentum
VALUE	Composite of cash flow yield, earnings yield and country relative sales-to-price ratio	Composite of forward price-to-earnings, price-to-book and enterprise value-to-operating cash flow	Composite of book value-to-price, earnings-to-price and sales-to-price	Ratio of fundamentals to capitalization weight
MOMENTUM	Cumulative 11 month returns	Combination of 6 and 12 month risk-adjusted excess return	12 month risk-adjusted price change excluding the most recent month	Combination of standard momentum, idiosyncratic momentum and fresh momentum
QUALITY	Composite of profitability, efficiency, earnings quality and leverage	Composite of ROE, debt-to-equity and earnings variability	Composite of ROE, accruals ratio and financial leverage ratio	Combination of high profitability and low investment

tifying stocks with high quality scores based on three main fundamental variables: high return on equity (ROE), stable year-over-year earnings growth and low financial leverage".[16] The latter defines quality as a "composite of profitability, efficiency, earnings quality and leverage" [17]. The data on the regressors are taken from the data library of Kenneth French, where we use the 5-factor model, including a market, size, value, profitability and investment factor, together with the momentum factor.[18] Contrary to the quality definition used in the quality indexes, these factors are part of standard multi factor asset pricing models that are extensively used and scrutinized in the academic literature, have a considerable post-publication record, and have been explained as compensation for risk.

Panel A of Exhibit 6 shows the results for the MQI and Panel B shows the results for the FQI. The first observation from these results is that the t-statistics point to a significant exposure to all the different factors, except from the

[15] These definitions are taken from:
<https://www.ftse.com/products/downloads/FTSE_Global_Factor_Index_Series_Methodology_Overview.pdf>,
<https://www.msci.com/factor-indexes>, <https://us.spindices.com/index-finder/> and
<https://www.researchaffiliates.com/en_us/strategies/rafi/rafi-multi-factor.html>
[16] See <https://www.msci.com/documents/10199/344aa133-d8fa-4a15-b091-20a8fd024b65>
[17] See <https://www.ftse.com/products/downloads/FTSE_Global_Factor_Index_Series_Methodology_Overview.pdf>
[18] See <http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html>

EXHIBIT 5

The Premium for Dividend Yield is Insignificant

Analysis is based on monthly total returns in USD for the period 30-Jun-1927 to 31-Dec-2016. All the data comes from the K. French data library. Numbers that are statistically significant (p-value less than 5%) are formatted in bold.

	PORTFOLIOS SORTED BY DIVIDEND YIELD					
US Long-Term	Low (Q1)	Quintile 2	Quintile 3	Quintile 4	High (Q5)	Q5 - Q1
Average Return	0.90%	0.94%	0.92%	1.08%	1.04%	0.14%
t-stat	-	-	-	-	-	1.07
CAPM MODEL						
Unexplained	-0.05%	0.05%	0.04%	**0.21%**	0.14%	-0.09%
Market Exposure	**1.05**	**0.94**	**0.94**	**0.93**	**0.97**	-0.08
R-squared	91.07%	92.24%	89.32%	86.50%	75.58%	0.93%
FAMA-FRENCH 3-FACTOR MODEL						
Unexplained	0.02%	0.08%	0.01%	0.14%	-0.01%	**-0.31%**
Market Exposure	**1.09**	**0.98**	**0.95**	**0.91**	**0.89**	**-0.20**
Size (SMB)	**-0.04**	**-0.14**	**-0.15**	**-0.13**	-0.04	0.01
Value (HML)	**-0.22**	**-0.05**	**0.15**	**0.25**	**0.54**	**0.76**
R-squared	92.79%	93.08%	90.87%	89.53%	85.02%	38.04%

EXHIBIT 6

Exposure of Composite Quality Factor Indexes excess returns to Standard Factors

Analysis is based on weekly return data for the period starting on 20 June 2002 and ending on 30 June 2018, for which we have data for both indexes. The first two columns of each panel show the regression betas together with their t-statistic. The third column shows how much of the annualized excess return of the index can be attributed to the different regressors based on their average returns and their exposures. The last column shows the relative size of the impact each of the factors had on the index excess returns, calculated as the absolute value of its performance attribution divided by the sum of the absolute values of the performance attributions.

Panel A: MSCI World Quality Index results

MSCI World Quality Index	Exposure (beta)	t-stat	Performance Attribution	Impact on Performance
Ann. alpha	0.01	1.75	0.96%	30.04%
Mkt	-0.06	-8.82	-0.47%	14.65%
Size	-0.20	-12.15	-0.29%	9.18%
Value	-0.26	-13.49	-0.31%	9.69%
Momentum	0.04	4.79	0.15%	4.64%
Profitability	0.39	15.01	1.01%	31.67%
Investment	0.00	-0.14	0.00%	0.12%
R^2	**64.06%**	**Total**	**1.04%**	**100.00%**

Panel B: FTSE Developed Quality Factor Index results

FTSE Developed Quality Factor Index	Exposure (beta)	t-stat	Performance Attribution	Impact on Performance
Ann. alpha	0.00	0.52	0.18%	10.86%
Mkt	-0.02	-5.31	-0.17%	10.26%
Size	0.02	1.76	0.03%	1.54%
Value	-0.19	-16.07	-0.22%	13.43%
Momentum	0.05	9.85	0.18%	11.11%
Profitability	0.27	17.80	0.72%	43.69%
Investment	0.15	9.02	0.15%	9.12%
R^2	**71.32%**	**Total**	**0.86%**	**100.00%**

investment factor in the MQI case and the size factor in the FQI case. As would be expected for a quality index, the exposures to profitability are the most clear with betas of 0.39 and 0.27.

However, for the MQI, the exposures to the market, size and value factors are also sizeable, but negative, with betas of -0.06, -0.20 and -0.26, respectively. For the FQI, we obtain similar results with a significantly negative beta of -0.02 and -0.19 for the market and value factors, respectively. Obtaining strong negative exposures to factors that are unrelated to quality is an important, presumably unintended, consequence of investing in these quality indexes. Apart from the market exposure for the FQI, these exposures are also larger in absolute value than the respective exposures to the investment factor, which would be expected to show a relatively stronger influence on a quality index. Instead, the investment exposure is estimated to be zero for the MQI. Clearly, the composite quality indexes expose an investor to a range of standard factors other than the quality-related profitability and investment factors.

When we look at the contribution of the different factors to the average annualized excess return of the indexes over the period, we see that for the two quality indexes, only 31.79% and 52.81% respectively of the impact on the excess returns comes from the quality-related factors profitability and investment. A large part of excess returns can be attributed to other standard factors or are unrelated to any factors. In fact, a big part of performance (30.04%) remains unexplained by any of the standard factors in the case of the FQI.

Taken together, these results show that the composite quality indexes are only moderately related to the academic profitability and investment factors, while a large part of their performance is either driven by other factors such as the market, or remain unexplained by the set of standard factors used in the model. An investor in these indexes will thus expose him- or herself to a large amount of unintended risk factors unrelated to quality.

This risk is present in any index based on non-standard factor definitions. Proprietary factor definitions lead to a risk of misunderstanding factor exposures. •

CONCLUSION: Reviving the Promise of Factor Investing

Factors used in investment practice show a stark mismatch with factors that have been documented by financial economists. Commercial factors are based on complex composite definitions that offer maximum flexibility. Providers use this flexibility to seek out the factors with the highest performance in a given dataset. Such practice allows spurious factors to be found. Spurious factors work well in a small dataset but will be useless in reality. Therefore, many factors that appear in popular investment products and analytic tools are likely false.

Even though many providers claim their factors are grounded in academic research, we have emphasized that two important conditions to support this claim are often not fulfilled. The factor definitions should have been used and validated across different independent studies and a risk-based explanation should support the existence of the factor. Without these assurances, there is no reason to assume the persistence of the factor.

We have also shown that relying on proprietary factor definitions can lead to unintended exposures. For example, investors who tilt towards a composite quality factor will end up with a strategy where, depending on the index we consider, only about one third or half of the excess returns are driven by exposure to the two well-documented quality factors (profitability and investment). This means that the part of the excess returns that is unrelated to quality factors can be as high as two-thirds, an obvious misalignment with the explicit choice to be exposed to quality factors (see Exhibit 6). Even if the quality factors perform as expected by the investor, this performance will not necessarily be reflected in portfolio returns, which are in a large part driven by other factors and idiosyncratic risks.

Available factor products thus do not deliver on the promise of factor investing, described almost a decade ago in the Norway study. Understanding the factor drivers of returns increases transparency and allows investors to formulate more explicit investment choices. However, being aware of exposures to useless factors, which have no reliable link with long-term returns, is equally useless.

A good idea can easily be distorted when implemented with poor tools. For a meaningful contribution to the ability of investors to make explicit investment choices, factor investing should focus on persistent and externally validated factors. It is time to recall the good idea of factor investing.

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A Defensive Offering that is Robust over the Long Term

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- **Scientific Beta's defensive offering relies on three different indexes to satisfy investors' various objectives and constraints.**
- **Our indexes are constructed based on the Smart Beta 2.0 framework and thus benefit from good diversification of unrewarded risks.**
- **The High Factor Intensity filter very strongly reduces the poor exposures of low volatility or minimum volatility strategies to other rewarded factors and as such, benefits from a much better excess return capacity over the long term.**
- **In line with the defensive objective, they deliver good levels of volatility reduction and capital protection in bear markets relative to the cap-weighted index.**
- **Compared to the popular MSCI Minimum Volatility index, they deliver much higher Sharpe ratios and information ratios as well as lower exposures to macroeconomic risks.**
- **For investors wary of rising interest rates, our sector-neutral index offers very low exposures to the T-Bill and Term Spread factors.**

Introduction

Factor investing offers a big promise. By identifying the Investors looking for defensive equity strategies want to participate in bullish markets while protecting their capital in bear periods by limiting their losses relative to the cap-weighted index. This concern for capital protection leads to equity investors usually investing in Low Volatility or Low Beta strategies, the main objectives of which are to offer defensive payoff profiles and to benefit from a superior risk-adjusted performance relative to cap-weighted indexes. The fact that a portfolio that is less risky than a cap-weighted index can generate outperformance on a risk-adjusted basis runs counter to the main financial theories, and it has been popularized under the name of Low Volatility anomaly.

The Low Volatility anomaly has its roots in the failure of the Capital Asset Pricing Model (CAPM) to explain the cross-section of expected returns. Indeed, according to the central prediction of the CAPM developed by Sharpe (1964) and Lintner (1965), there is a linear relationship between systematic risk or market beta and expected returns. However, this prediction was soon contradicted by many academic publications, Friend and Blume (1970), Black, Jensen and Scholes (1972), Miller and Scholes (1972) and Haugen and Heins (1972, 1975), highlighting a negative or flat relationship between systematic risks and expected returns in the cross-section of stock returns. Following the work of Black (1972), Frazzini and Pedersen (2014) derive an equilibrium model that provides a risk-based justification of the Low Volatility anomaly. One major prediction of their model is that a "betting against beta" (BAB) strategy, that goes long low-beta assets and short high-beta assets, adjusting both legs with leverage to have a market neutral portfolio, produces significant positive risk-adjusted returns that are not explained by the size, value and momentum effects of Fama and French (1992, 1993) and of Jegadeesh and Titman (1993). They show that the poor returns of the BAB strategy occur when funding constraints become tight, which is consistent with liquidity-constrained investors having to sell leveraged positions in low-risk assets in bad times.

Several other academic works provide the same finding on persistence and existence of the Low Volatility anomaly on US and international universes. Ang et al. (2006, 2009) show that stocks with high recent idiosyncratic volatility have low average returns that are not explained by standard risk factors (size, value, momentum). Finally, Blitz and van Vliet (2007) show that low volatility stocks have higher risk-adjusted returns than high volatility stocks and that standard risk factor cannot explain the alpha resulting from a long/short portfolio. Overall, the Low Volatility anomaly is one of the strongest risk factors found in the academic literature (along with size, value, momentum, low investment and high profitability), with a strong annual premium of 8.7% over the period 1926 to 2012 (Frazzini and Pedersen, 2014).

There are two main approaches to benefit from the "Low Volatility" factor reward and obtain a defensive portfolio based on i) Modern Portfolio Theory and ii) factor investing. The former approach tries to build the portfolio with the lowest risk on the efficient frontier (Markowitz, 1952) by combining stocks with low volatilities and low pairwise correlations. This minimum volatility portfolio, achieved through an optimization, is known to produce very concentrated portfolios. This is why most commercial solutions use very tight constraints (like min-max weights) to force the optimizer to generate less concentrated allocations. Moreover, optimizers, used to solve minimum volatility allocations, are very sensitive to outliers and to parameter estimation errors that can lead to dramatic changes to the optimal weights leading to high turnover and sub-optimal allocations that does not reach minimum volatility ex-post.

The second approach is the one we pursue at Scientific Beta for harvesting rewarded risk factors. The Smart Beta 2.0 framework is the cornerstone of the construction of our smart factor indexes. It favors clear separation of the stock selection and weighting phases. The stock selection objective is to expose the portfolio towards a desired and rewarded factor tilt, like the Low Volatility factor, and the weighting objective is to diversify away idiosyncratic risks in order to obtain a well-diversified portfolio. The latter is key to achieving the highest possible risk-adjusted performance over the long-term. Amenc et al. (2012) shows that this approach is more robust for achieving well-diversified defensive portfolios that produce a similar level of outperformance with higher risk reduction than portfolios based solely on Modern Portfolio Theory.

Scientific Beta's defensive offering relies on three types of indexes to address the various objectives of investors:

i. The High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy) index;
ii. The High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy) (Sector Neutral) index;
iii. The Narrow High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy) index.

The objective of the first (standard HFI) index is to be exposed to the Low Volatility factor in order to provide a reduction in volatility compared to the cap-weighted index and to provide protection in bear markets. Moreover, it aims to maintain high factor intensity by using a High Factor Intensity (HFI) filter and deliver the best risk-adjusted performance through the diversification of idiosyncratic risks. This index is clearly defensive, since it offers good risk reduction and capital protection while benefiting from a high risk-adjusted performance over the long-term, due to its strong factor intensity.

The second (sector neutral HFI) index has two main objectives. The first one is to provide exposure to the Low Volatility factor. The second one is to deliver low relative risks compared to the cap-weighted index through a sector-neutral objective. The latter implies that the index will have less exposure to the Low Volatility factor than the standard HFI index and consequently a lower reduction of volatility and less protection in bear markets. Nonetheless, we will show that the index delivers better relative performance and lower exposure to interest rate risks, because of its reduced sector deviations relative to the cap-weighted index. The latter can be suitable for investors seeking to benefit from both defensive characteristics and rewards of the Low Volatility factor but who are worried by the unexpected consequences of minimum volatility strategies' exposures to fixed income risks.

Finally, the last (Narrow HFI) index is for investors who seek the highest factor exposure to the Low Volatility factor through a narrow selection of low volatile stocks. Its objectives are similar to the standard HFI index, but the narrow selection increases the concentration to the Low Volatility factor thus increasing the defensiveness and hence the protection in bear markets. It comes at the cost of lower exposures to other rewarded risk factors and important losses in bull markets. This index can be used in overlay strategies that target the modification of the global exposure of a portfolio with only a limited investment in a smart factor index.

The rest of the article is organized as follows. In Section 1, we discuss our construction philosophy based on the Smart Beta 2.0 framework and the way we tackle negative factor interaction with the HFI filter. We also present our defensive offering in more detail. In the following sections, we compare our offering to the MSCI Minimum Volatility index on two universes: SciBeta USA and SciBeta Developed. More particularly, in Section 2, we show that our offering delivers a better risk-adjusted performance and a better volatility reduction compared to the cap-weighted index. In Section 3, we show that our offering has a high factor intensity and good factor deconcentration. In Section 4, we show that our offering improves relative performance, extreme relative risks and probabilities of outperformance. In Section 5, we show that our offering delivers good protection in bear markets. In Section 6, we analyze the macroeconomic sensitivity of our offering, such as interest rates or credit spreads and show that our offering has weaker sensitivities, in particular our sector neutral HFI index. Finally, Section 7 concludes.

1.Robust Smart Factor Design

A key element in Scientific Beta smart factor index design is that each index not only tilts towards a desired factor, but also achieves a sound level of diversification of specific risk, in keeping with the Smart Beta 2.0 methodology introduced by Amenc and Goltz (2013) (see Exhibit 1).

1.1.Stock selection

Focusing only on stocks with the highest factor scores ignores the potential negative interaction effects with other risk factors. For instance, a stock with a low volatility score might have a low value score. A smart factor index might therefore have a positive exposure to a desired factor tilt but low or even negative exposures to other rewarded risk factors. Thus, investors would benefit from additional controls in the stock selection mechanism to account for such interaction effects. To address the issue of factor interactions, we follow the approach proposed by Amenc et al. (2017), which differentiates from standard "bottom-up" approaches. The authors document that the "top-down" approach provides better performance per unit of factor exposure due to better diversification. They demonstrate a solution to increase factor intensity in the "top-down" approach by eliminating stocks with low multi-factor scores. They show that the absolute underperformance of a "factor losers" portfolio is substantially larger than the outperformance of a "factor champions" portfolio. Therefore, eliminating factor losers may be a more efficient way to increase factor intensity than focusing on factor champions, which is the milestone of "bottom-up" approaches.

Scientific Beta uses a factor intensity (HFI) filter, which eliminates stocks with the lowest multi-factor scores. The score is based on the following factors: value, momentum, low volatility, high profitability and low investment. In Exhibit 2a, we show the standard selection process that we use for our smart factor indexes. We select 50% of stocks based on the factor score and excludes stocks, within the factor-based selection, with the lowest multi-factor score, leaving 30% of stocks compared to the starting investment universe.

The HFI filter is available on our defensive indexes and is essential to maintain a good factor intensity. Indeed, when investing in a Low Volatility smart factor, the objective is to increase the defensiveness of its portfolio and to benefit from the long-term reward of the factor, while preserving its current factor exposures that are the main driver of its portfolio long-term performance. In Exhibit 2b, we show the factor exposures of two Low Volatility indexes on SciBeta US universe, with and without the HFI filter. We highlight that the index benefiting from the HFI filter has the same exposure to the Low Volatility factor but a positive exposure to the other risk factors. Therefore, when added to a portfolio, it will not deteriorate its existing factor exposures.

Note that the HFI filter is built with a dynamic adjustment, which takes into account the relative distance of the score of the whole of the universe compared to the score of the factor under consideration, which is not possible when using "bottom-up" approaches, which are based uniquely on scores or ranks. The ultimate objective is to preserve the factor intensity in its factor diversity.

To obtain more exposure to the desired factor tilt, we also have an alternative process, which starts with a narrower stock selection, which contains only 30% of stocks in the entire universe, and filters out a smaller number of stocks, leaving 20% of stocks compared to the starting investment universe at the end of the process (see Exhibit 2c). The Narrow HFI filter corresponds to investors favoring the highest factor exposure to a desired factor tilt.

1.2. Diversification weighting scheme

Selecting stocks based on factor characteristics is only the first step in the Smart Beta 2.0 framework. The second step consists in diversifying away idiosyncratic risks to obtain a well-diversified portfolio and the highest possible risk-adjusted performance. To achieve this objective, we need to choose a diversifying weighting scheme.

Scientific Beta's approach is to combine four different weighting schemes, as explained in Exhibit 3, in order to diversify model risks. The diversified multi-strategy weighting scheme equally weights the following strategies: efficient maximum Sharpe ratio, maximum deconcentration, maximum decorrelation and diversified risk-weighted. Amenc et al. (2015) show that diversifying across different models improve the robustness of smart

EXHIBIT 1

Smart Beta 2.0 framework

EXHIBIT 2A

Stock selection with HFI filter

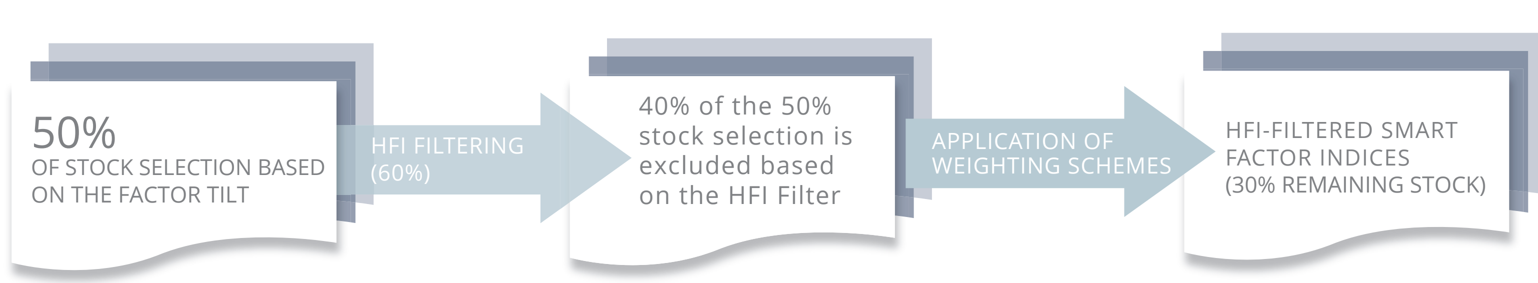

EXHIBIT 2B

Factor exposures of two Low Volatility indexes with and without the HFI filter

The analysis is based on daily total returns in USD from 21-Jun-2002 (base date of SciBeta indexes) to 31-Dec-2018. Yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. The regression is based on weekly total returns. The Market factor is the excess return series of the cap-weighted index over the risk-free rate. The cap-weighted index is the SciBeta USA Cap-Weighted. The other six factors are equal-weighted daily-rebalanced factors obtained from Scientific Beta and are beta-adjusted every quarter with their realized CAPM beta. Coefficients significant at 5% p-value are highlighted in bold. The smart factor indexes used are the SciBeta USA Low Volatility Diversified Multi-Strategy and the SciBeta USA High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy).

21-Jun-2002 to 31-Dec-2018 (RI/USD)	SciBeta US Low Volatility Diversified Multi-Strategy	SciBeta US HFI Low Volatility Diversified Multi-Strategy (4-Strategy)
Unexplained	0.01	0.01
Market Factor	**0.83**	**0.79**
Size (SMB) Factor	**0.11**	**0.07**
Value (HML) Factor	-0.02	**0.10**
Momentum (MOM) Factor	-0.01	**0.06**
Volatility Factor	**0.28**	**0.29**
Profitability Factor	-0.02	**0.08**
Investment Factor	0.02	**0.05**
Factor Intensity	**0.37**	**0.65**

EXHIBIT 2C

Stock selection with HFI filter

beta strategies, because the risk of choosing one specific weighting scheme is not rewarded.

Since each weighting scheme is different in terms of parameter estimation risk and optimality risk, investors can improve the diversification of model risks by combining several weighting schemes and avoid, for instance, the high sensitivity of minimum volatility approaches to the estimation of risk parameters.

1.3. Scientific Beta defensive offering design

Scientific Beta's offering design is aimed at providing investors with a defensive profile, i.e. lower volatility compared to the cap-weighted index, as well as protection in bear markets. Moreover, we want to offer them different choices that will fit with their various investment objectives. Indeed, some investors might be interested to have the lowest volatility and the highest protection in bear markets without any regards for tracking error. Others might want to have the smallest volatility while keeping a low tracking error, whereas some investors might want to have a good volatility reduction and protection in bear markets but with the highest possible risk-adjusted returns. Therefore, our defensive offering relies on three different indexes that will give different level of exposure to the Low Volatility factor, and consequently different level of defensiveness, factor intensity, risk-adjusted performance and relative risks, to fit investors' preferences.

1.3.1. High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy)

This is the flagship index of the offering (hereafter the "standard HFI index"). Its design is similar to our flagship multi-beta multi-strategy offering. Its construction follows the one described in Exhibit 2a. It seeks an exposure to the Low Volatility factor through the selection of 50% of stocks of the universe with the lowest volatility. The use of the HFI filter, which allows to take into account the negative factor interaction between factors, removes 40% stocks with the lowest multi-factor scores (based on Value, Momentum, Low Volatility, High Profitability and Low investment scores), leading to a final selection of 30% of the size of the original universe. Finally, we apply the diversified multi-strategy weighting scheme described in Section 1.2 to diversify away idiosyncratic risks. This index is aimed at investors seeking the highest risk-adjusted performance with a high factor intensity and a good reduction of volatility and protection in bear markets compared to the cap-weighted index.

1.3.2. High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy) (Sector Neutral)

It is well known that smart factors are exposed to implicit risks (see Shirbini, 2018) and in particular sector risks (see Aguet et al. 2018) that can have important consequences on short-term performances. Therefore, the design of this index (called sector neutral HFI index in the rest of the paper) is similar to our standard HFI index but with an additional sector neutral objective, to control sector risks and reduce relative risks like tracking error. The index seeks an exposure to the Low Volatility factor through the selection, within each sector, of 50% of stocks with the lowest volatility. The use of the HFI filter, which allows to take into account the negative factor interaction between factors, removes 40% stocks with the lowest multi-factor scores, leading to a final selection of 30% of the size of the original universe. Finally, we apply the diversified multi-strategy weighting scheme described in Section 1.2 to diversify away idiosyncratic risks. The index is aimed at investors that cares about tracking error or relative risks, while seeking a reduction of volatility and protection in bear markets relative to the cap-weighted index. Obviously, the sector neutrality objective, since it reduces the distance of the smart factor to the cap-weighted index, has a cost. Indeed, the exposure to the Low Volatility factor and the overall factor intensity of the index will be weaker than without sector neutrality, which is the case of the standard HFI index. Nevertheless, its benefits reside in a lower tracking error, higher information ratio and low exposures to macroeconomic factors and in particular to interest rate risks.

1.3.3. Narrow High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy)

The construction of this index (hereafter referred to as

EXHIBIT 3

Multi-Strategy diversification scheme

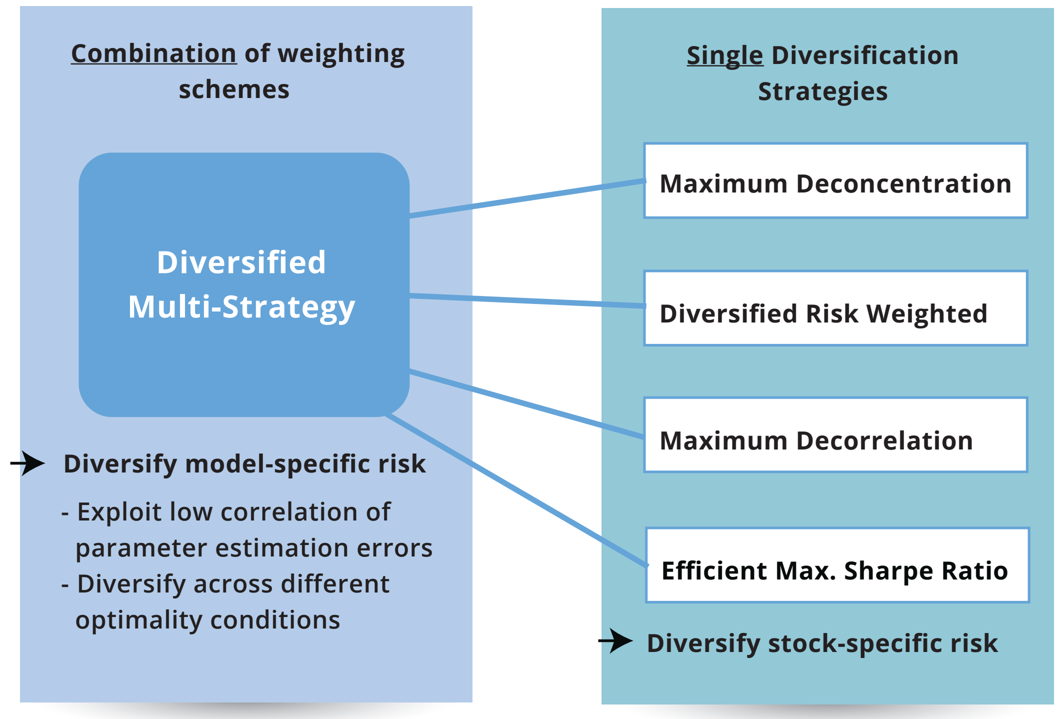

EXHIBIT 4

Absolute performance of SciBeta Defensive offering and MSCI Minimum Volatility on SciBeta USA and SciBeta Developed universes.
The analysis is based on daily total returns in USD from 21-Jun-2002 (base date of SciBeta indexes) to 31-Dec-2018. All statistics are annualized. Yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. The smart factor indexes used are the SciBeta USA High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy), SciBeta USA High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy) (Sector Neutral), SciBeta USA Narrow High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy), SciBeta Developed High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy), SciBeta Developed High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy) (Sector Neutral) and the SciBeta Developed Narrow High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy). The cap-weighted indexes are the SciBeta USA Cap-Weighted and the SciBeta Developed Cap-Weighted.

21-Jun-2002 to 31-Dec-2018 (RI/USD)	CW Index	Standard HFI	Sector Neutral HFI	Narrow HFI	MSCI Min Vol
Panel A - SciBeta USA					
Ann. Returns	8.14%	10.80%	10.60%	9.85%	8.87%
Ann. Volatility	18.61%	14.80%	15.81%	13.96%	15.51%
Volatility Reduction	-	-21%	-15%	-25%	-17%
Sharpe Ratio	0.37	0.64	0.59	0.62	0.49
Sortino Ratio	0.52	0.92	0.84	0.87	0.69
Max Drawdown	54.6%	43.5%	46.3%	43.1%	46.6%
Extreme 3Y Rolling Volatility	40.9%	31.9%	33.6%	30.2%	35.0%
Panel B - SciBeta Developed					
Ann. Returns	7.40%	10.65%	10.21%	10.17%	8.39%
Ann. Volatility	15.51%	12.10%	12.75%	11.44%	11.54%
Volatility Reduction	-	-35%	-31%	-39%	-38%
Sharpe Ratio	0.40	0.78	0.70	0.78	0.62
Sortino Ratio	0.55	1.08	0.98	1.08	0.86
Max Drawdown	57.1%	46.2%	47.4%	44.3%	47.7%
Extreme 3Y Rolling Volatility	32.3%	25.2%	26.5%	24.0%	25.6%

the "Narrow HFI index") seeks a strong exposure to the Low Volatility factor through the selection of 30% of stocks (narrow selection) of the universe with the lowest volatility (see Exhibit 2c). The use of the HFI filter, which allows the negative factor interaction between factors to be taken into account, removes one-third of stocks with the lowest multi-factor scores, leading to a final selection of 20% of the size of the original universe. Finally, we apply the diversified multi-strategy weighting scheme described in Section 1.2 to diversify away idiosyncratic risks. This index is aimed at investors seeking the highest exposure to the Low Volatility factor to obtain the highest reduction of volatility compared the cap-weighted index and obtain the highest protection in bear markets, while having a strong factor concentration, a high tracking error and strong losses in bull markets. Nonetheless, we highlight that the use of the HFI filter avoids a factor over concentration, which is the risk of traditional high concentrated minimum volatility portfolio, and maintains a relatively good factor intensity.

2. High Risk-Adjusted Performance and Strong Volatility Reduction

Due to the combination of the HFI filter and the stock selection based on low volatility, our defensive indexes offer very good risk-adjusted performances and strong volatility reduction compared to the cap-weighted index, as seen in Exhibit 4. Indeed, we observe in Panel A (US universe) that our indexes have Sharpe ratios ranging from 0.59 to 0.64, which corresponds to an improvement of 60% and 74% compared to the cap-weighted index and 20% and 31% compared to the MSCI Minimum Volatility index. The volatility reductions range from 15% and 25% whereas the MSCI index offers a reduction of 17%, which is only slightly higher than our sector-neutral HFI index. Due to the good overall factor intensity, that avoids factor concentration issues, and the diversification of specific risk, we observe a reduction in extreme risks, since maximum drawdown and extreme 3-Year rolling volatility statistics are strongly reduced in comparison to the cap-weighted index. We also highlight that the extreme risk statistics of our three defensive indexes are better than those of the MSCI index.

We have similar conclusions on Panel B (Developed universe). Indeed, we observe that our indexes have Sharpe ratios ranging from 0.70 to 0.78, which corresponds to an improvement of 77% and 97% compared to the cap-weighted index and 14% and 26% compared to the MSCI Minimum Volatility index. The volatility reductions are ranging from 31% and 39%, which are in the same range as the MSCI index (reduction of 38%). We also observe a reduction in extreme risks, since maximum drawdown and extreme 3-Year rolling volatility statistics are strongly reduced in comparison to the cap-weighted index.

Overall, our three defensive indexes have very clear behavior. The standard HFI index offers a similar level of volatility reduction as the MSCI Minimum Volatility index, but with a much higher Sharpe ratio, which is the highest of our offering. The sector neutral HFI index offers the weakest volatility reduction and the smallest Sharpe ratio of our offering because its objective is to control sector

EXHIBIT 5

Factor exposures of SciBeta Defensive offering and MSCI Minimum Volatility on SciBeta USA and SciBeta Developed universes

The analysis is based on daily total returns in USD from 21-Jun-2002 (base date of SciBeta indexes) to 31-Dec-2018. All statistics are annualized. Yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. The regression is based on weekly total returns. The Market factor is the excess return series of the cap-weighted index over the risk-free rate. The cap-weighted indexes are the SciBeta USA Cap-Weighted and the SciBeta Developed Cap-Weighted. The other six factors are equal-weighted daily-rebalanced factors obtained from Scientific Beta and are beta-adjusted every quarter with their realized CAPM beta. Coefficients significant at 5% p-value are highlighted in bold. The Factor Deconcentration (ENF) statistic is the inverse of the sum of squared of normalized factor betas, where the latter is the factor beta divided by the sum of factor betas. The Factor Exposure Quality is the multiplication of the Factor Intensity and the Factor Deconcentration. The smart factor indexes used are the SciBeta USA High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy), SciBeta USA High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy) (Sector Neutral), SciBeta USA Narrow High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy), SciBeta Developed High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy), SciBeta Developed High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy) (Sector Neutral) and the SciBeta Developed Narrow High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy).

21-Jun-2002 to 31-Dec-2018 (RI/USD)	Standard HFI	Sector Neutral	Narrow HFI HFIa	MSCI Min Vol
Panel A - SciBeta USA				
Ann. Unexplained	0.01	**0.02**	0.00	0.00
Market Beta	**0.79**	**0.86**	**0.72**	**0.81**
SMB* Beta	**0.07**	**0.05**	**0.06**	**0.05**
HML* Beta	**0.10**	**0.15**	**0.12**	-0.04
MOM* Beta	**0.06**	**0.07**	**0.04**	**-0.02**
Low Vol* Beta	**0.29**	**0.16**	**0.41**	**0.32**
High Prof* Beta	**0.08**	**0.08**	0.00	**-0.04**
Low Inv* Beta	**0.05**	0.01	0.01	**-0.06**
R Sqrd	95.9%	96.6%	94.6%	95.6%
Factor Intensity (Int)	0.65	0.52	0.65	0.19
Factor Deconc. (ENF)	3.81	4.36	2.28	0.34
Factor Exp. Quality (Int x ENF)	2.47	2.24	1.48	0.06
Panel B - SciBeta Developed				
Ann. Unexplained	0.01	0.01	0.00	-0.01
Market Beta	**0.77**	**0.82**	**0.72**	**0.71**
SMB* Beta	**0.09**	**0.08**	**0.08**	**0.10**
HML* Beta	**0.08**	**0.13**	**0.07**	**-0.12**
MOM* Beta	**0.05**	**0.07**	**0.04**	**-0.05**
Low Vol* Beta	**0.32**	**0.22**	**0.44**	**0.42**
High Prof* Beta	**0.08**	**0.08**	0.00	-0.05
Low Inv* Beta	0.03	-0.03	-0.02	-0.04
R Sqrd	97.5%	98.0%	96.8%	94.5%
Factor Intensity (Int)	0.65	0.56	0.60	0.26
Factor Deconc. (ENF)	3.33	3.69	1.78	0.33
Factor Exp. Quality (Int x ENF)	2.18	2.08	1.07	0.09

EXHIBIT 6

Relative performance of SciBeta Defensive offering and MSCI Minimum Volatility on SciBeta USA and SciBeta Developed universes

The analysis is based on daily total returns in USD from 21-Jun-2002 (base date of SciBeta indexes) to 31-Dec-2018. All statistics are annualized. Yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. The smart factor indexes used are the SciBeta USA High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy), SciBeta USA High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy) (Sector Neutral), SciBeta USA Narrow High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy), SciBeta Developed High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy), SciBeta Developed High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy) (Sector Neutral) and the SciBeta Developed Narrow High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy). The cap-weighted indexes are the SciBeta USA Cap-Weighted and the SciBeta Developed Cap-Weighted.

21-Jun-2002 to 31-Dec-2018 (RI/USD)	Standard HFI	Sector Neutral	Narrow HFI HFI	MSCI Min Vol
Panel A - SciBeta USA				
Ann. Rel. Returns	2.66%	2.46%	1.71%	0.73%
Ann. Tracking Error	6.04%	4.56%	7.48%	5.25%
Information Ratio	0.44	0.54	0.23	0.14
Max Rel. DD	11.9%	9.5%	17.7%	13.7%
Outperf Prob (1Y)	65.10%	69.30%	52.65%	48.09%
Outperf Prob (3Y)	91.09%	92.08%	81.75%	67.47%
Outperf Prob (5Y)	96.02%	91.38%	82.42%	68.49%
Panel B - SciBeta Developed				
Ann. Rel. Returns	3.24%	2.81%	2.76%	0.99%
Ann. Tracking Error	4.89%	3.89%	5.93%	6.04%
Information Ratio	0.66	0.72	0.47	0.16
Max Rel. DD	10.8%	9.0%	15.0%	17.3%
Outperf Prob (1Y)	65.60%	72.38%	57.34%	46.61%
Outperf Prob (3Y)	97.88%	99.15%	88.40%	68.32%
Outperf Prob (5Y)	100.00%	100.00%	95.19%	71.97%

risks and therefore improve relative risks (we will discuss this point in Section 4). Nonetheless, it offers only a slightly lower volatility reduction than the MSCI Minimum Volatility index (-15% vs -17% on US universe and -31% vs -38% on Developed universe) but with a higher Sharpe ratio (+20% on US and +14% on Developed universe). Finally, the Narrow HFI index (Narrow HFI Low Volatility Diversified Multi-Strategy) offers the highest volatility reduction and the lowest level of extreme risks, which is its main objective. Moreover, it delivers slightly reduced Sharpe ratio as our standard HFI index.

3. High Factor Intensity and Good Factor Deconcentration

The very good risk-adjusted performance of our defensive indexes finds its roots in factor intensity. Indeed, we observe in Exhibit 5 that our indexes have much higher factor intensities than the MSCI Minimum Volatility index while having a good exposure to the Low Volatility factor. This is the main benefit of the HFI filter that we use in our construction process.

In Panel A (US universe), we observe that factor intensities of our indexes are ranging between 0.52 to 0.65, which is an improvement of 166% and 236% compared to the MSCI Minimum Volatility index. Exposures to the Low Volatility factor are ranging between 0.16, for the sector neutral HFI index to 0.41 for the Narrow HFI index. In between, we find the standard HFI index with an exposure of 0.29. The sector neutrality objective explains the low exposure of the sector neutral index, which dilutes the Low Volatility exposure. Nevertheless, the index is still well exposed to other rewarded risk factors and therefore has a good factor intensity. We highlight that our indexes have no negative exposures to any rewarded risk factors whereas the MSCI Minimum Volatility index has negative exposures that are statistically significant to Momentum, High Profitability and Low Investment, which translates into a poor factor intensity of only 0.19. Moreover, its Low Volatility exposure is similar to our standard HFI index but 20% lower than our Narrow HFI index. The factor deconcentration, which is the effective number of factor to which the index is exposed and the factor exposure quality are much higher for our indexes than the MSCI index, which is the result of better exposures to rewarded risk factors. Finally, the level of market beta exposures reflect the defensiveness of our indexes. The Narrow HFI index, which has the highest Low Volatility exposure has also the lowest market beta exposure (0.72), explaining why it has the highest level of volatility reduction (Exhibit 4). Our sector neutral index has the highest market beta exposure (0.86) and is therefore the least defensive index of our offering but its objective is to reduce relative risks compared to the cap-weighted index, so it was expected. Finally, our standard HFI index has a market beta exposure of 0.79, which is similar to the MSCI Minimum Volatility index.

We have similar conclusion on Panel B (Developed universe). Indeed, we observe that factor intensities of our indexes are ranging from 0.56 to 0.65, which is an improvement of 115% to 150% compared to the MSCI Minimum Volatility index. Exposures to the Low Volatility factor are ranging between 0.22, for the sector neutral HFI index to 0.44 for the Narrow HFI index. In between, we find the standard HFI index with an exposure of 0.32. We highlight that our indexes have almost no negative exposures to any rewarded risk factors whereas the MSCI Minimum Volatility index has negative exposures that are statistically significant to Value and Momentum, which translates into a poor factor intensity of only 0.26. The factor deconcentration and the factor exposure quality are much higher for our indexes than the MSCI index, which is the result of better exposures to rewarded risk factors. In terms of market beta exposures, the Narrow HFI index has the lowest one (0.72), which is similar to the MSCI Minimum Volatility index. Our sector neutral index has the highest market beta (0.82) because of the sector neutrality objective. Finally, our standard HFI index has a market beta exposure of 0.77, which unlike to the US universe is higher than the MSCI index.

4. High Information Ratio and Robustness of Outperformance

Our defensive offering has very good relative performance compared to the cap-weighted index as well as strong probability of outperformance as seen in Exhibit 6. Indeed, we observe in Panel A (US universe) that our indexes have information ratios ranging from 0.23, for our Narrow HFI index, to 0.54 for our sector neutral HFI index. These numbers are much higher than the MSCI Minimum Volatility index, which delivers an information ratio of only 0.14. The probabilities of outperformance for each horizon are also much better for our indexes, which demonstrates the robustness of our construction process based on the Smart Beta 2.0 framework. The sector neutral HFI index clearly exhibits the best relative statistics, since it is one of its objective to reduce the distance to the cap-weighted index. It exhibits the strongest probabilities of outperformance for the 1-Year and 3-Year horizon and the lowest maximum relative drawdown. The standard HFI index has a good information ratio, which is more than 200% higher than the MSCI index with only a slightly higher tracking error. It also exhibits high probabilities of outperformance, especially at the 5-Y horizon and has weaker extreme risks

EXHIBIT 7

Relative conditional performance based on bull/bear market return regimes of SciBeta Defensive offering and MSCI Minimum Volatility on SciBeta USA and SciBeta Developed universes

The analysis is based on daily total returns in USD from 21-Jun-2002 (base date of SciBeta indexes) to 31-Dec-2018. All statistics are annualized. Yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. Bull regimes are defined as months with positive performance of the cap-weighted index. Bear regimes are defined as months with negative performance of the cap-weighted index. Coefficients significant at 5% p-value are highlighted in bold. The smart factor indexes used are the SciBeta USA High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy), SciBeta USA High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy) (Sector Neutral), SciBeta USA Narrow High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy), SciBeta Developed High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy), SciBeta Developed High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy) (Sector Neutral) and the SciBeta Developed Narrow High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy). The cap-weighted indexes are the SciBeta USA Cap-Weighted and the SciBeta Developed Cap-Weighted.

21-Jun-2002 to 31-Dec-2018 (RI/USD)	Standard HFI	Sector Neutral	Narrow HFI HFI	MSCI Min Vol
Panel A - SciBeta USA				
Bull Rel. Ret	-5.26%	-2.43%	-9.59%	-8.33%
Bear Rel. Ret	10.79%	7.23%	13.97%	10.40%
Rel. Bull/Bear Spread	**-16.04%**	**-9.66%**	**-23.56%**	**-18.73%**
Panel B - SciBeta Developed				
Bull Rel. Ret	-5.81%	-3.90%	-9.45%	-12.80%
Bear Rel. Ret	11.24%	8.54%	14.06%	14.09%
Rel. Bull/Bear Spread	**-17.05%**	**-12.45%**	**-23.51%**	**-26.89%**

than the MSCI index (11.9% vs 13.7%). Finally, the Narrow HFI index has logically the highest tracking error. Indeed, its objective is to achieve the strongest volatility reduction relative to the cap-weighted index, this is only possible with a high tracking error. Consequently, it also delivers the smallest information ratio (0.23) and the lowest probabilities of outperformance of our offering. Nevertheless, except for tracking error and maximum relative drawdown, it has better statistics than the MSCI index. This means that for a lower level of absolute risk, the Narrow HFI index delivers a better performance compared to the MSCI index.

We have even stronger conclusions on Panel B (Developed universe). Indeed, we observe that our indexes have information ratios ranging from 0.47, for our Narrow HFI index, to 0.72 for our sector neutral HFI index. These numbers are much higher than the MSCI Minimum Volatility index, which delivers an information ratio of only 0.16 (very similar to Panel A). The probabilities of outperformance for each horizon are also much higher for our indexes. They reach 100% at the 5-Year horizon for our standard HFI and sector neutral HFI indexes and are very close to 100% at the 3-Year horizon. These numbers again demonstrate the robustness of our construction process. The sector neutral HFI index clearly exhibits the best relative statistics, since it has the highest information ratio (+342% compared to the MSCI index), the strongest probabilities of outperformance at each horizon, the lowest maximum relative drawdown and the lowest tracking error (which is 36% lower than the MSCI index). The standard HFI index has a good information ratio, which is more than 305% higher than the MSCI index with even a smaller tracking error (-19%) and weaker maximum relative drawdown (10.8% versus 17.3%). Finally, the Narrow HFI index has the smallest information ratio and probabilities of outperformance and the highest relative risks of our offering, but its statistics are still better in comparison to the MSCI index.

5. Good Protection in Distressed Markets

Conditional performance is an interesting tool to assess the robustness of smart beta strategies. Indeed, they are, by construction, more or less dependent to some market or macro regimes. Defensive solutions provide, by construction, protection in bear markets, therefore there relative returns should be highly sensitive to market regimes.

In this section, we analyze the conditional performance of our offering given three different types of regimes: bull/bear market return regimes, low/high volatility market regimes and bull/bear Low Volatility return regimes.

We start the analysis with bull/bear market regimes conditional analysis (see Exhibit 7). We first observe a clear asymmetry of relative returns compared to the cap-weighted index, since they are negative in bull markets and positive in bear markets while they are much higher in magnitude in bear markets. This is the typical characteristics of defensive strategies.

The Narrow HFI index provides, as expected, the strongest protection in bear markets, since its relative return stands at +13.97% on US and +14.06% on Developed, but it also provides the lowest relative return in bull markets (-9.59% and -9.45% on US and Developed universes respectively).

The standard HFI index offers also a good protection in bear markets, since its relative return stands at +10.79% on US, which is similar to the MSCI Minimum Volatility index (+10.4%) and +11.24% on Developed, which is slightly lower than the MSCI index (+14.09%). However, in bull markets, the index loses only -5.26% relative to the cap-weighted index on US and -5.81% on Developed, which is much better than the MSCI index (relative loss of -8.33% and -12.8% on US and Developed universes respectively).

Finally, the sector neutral HFI index provides the lowest level of protection in bear markets with a relative returns standing at +7.23% on US and +8.54% on Developed. Note that the protection is still interesting since it is only 33% and 24% lower than the standard HFI index, on both. In bull markets, the index loses only -2.43% compared to the cap-weighted index on US and -3.9% on Developed.

As expected, the sector neutral HFI index delivers the lowest protection in bear markets and is, as expected, less sensitive to market regimes, since it provides the smallest bull/bear spread relative return of all indexes. At the opposite, the Narrow HFI index offers the highest protection in bear markets and suffers important relative losses in bull markets. The standard HFI index is a good compromise, since it provides good level of protection in bear markets, almost as high as the Narrow HFI index and has more controlled relative losses in bull markets. Moreover, for the same level of protection in bear markets if suffers smaller relative losses in bull markets than the MSCI index, due to its better factor intensity.

Next, we analyze the performance of our indexes in low and high volatility market regimes (see Exhibit 8). As in Exhibit 7, we observe the same asymmetry of relative returns between low volatile and high volatile regimes, which is consistent with the defensive bias of the indexes. The Narrow HFI index offers the highest protection in high volatile markets since its relative return stands at +7.96% on US and +8.36% on Developed, but delivers the lowest relative return of our offering in low volatile markets (-6.16% and -4.24% on US and Developed). Nevertheless, we highlight that the MSCI Minimum Volatility index does even worse with a relative loss of -7.08% in low volatile markets on the US universe and -7.63% on Developed.

The standard HFI index provides a good level of protection in high volatile markets since its relative return stands at +6.55% on US and +7.26% on Developed, which is similar to the MSCI index (+6.99% and +7.95% on US and Developed). In low volatile markets, it loses -2.35% compared to the cap-weighted index on US and -1.84% on Developed, which is much better than the MSCI index (relative loss of -7.08% and -7.63% on US and Developed universes respectively).

The sector neutral HFI index has the lowest protection in high volatile markets with a relative return of +5.05% on US and +5.63% on Developed, which is only 23% lower than the standard HFI index on both universes and has the smallest relative loss in low volatile markets (-0.87% on US and -0.77% on Developed).

These results are similar with the bull/bear market return regimes analysis. The sector neutral HFI index delivers the lowest protection in low volatile markets but its relative performance is less conditional to market volatility regimes. At the opposite, the Narrow HFI index offers the strongest protection in high volatile markets and suffers important relative losses in low volatile markets. The

EXHIBIT 8

Relative conditional performance based on bull/bear market volatility regimes of SciBeta Defensive offering and MSCI Minimum Volatility on SciBeta USA and SciBeta Developed universes

The analysis is based on daily total returns in USD from 21-Jun-2002 (base date of SciBeta indexes) to 31-Dec-2018. All statistics are annualized. Yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. Months in which the volatility of the cap-weighted index is greater than the median volatility across all months are classified as high volatility regimes. Months in which the volatility of the cap-weighted index is lower than the median volatility across all months are classified as low volatility regimes. Coefficients significant at 5% p-value are highlighted in bold. The smart factor indexes used are the SciBeta USA High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy), SciBeta USA High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy) (Sector Neutral), SciBeta USA Narrow High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy), SciBeta Developed High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy), SciBeta Developed High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy) (Sector Neutral) and the SciBeta Developed Narrow High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy). The cap-weighted indexes are the SciBeta USA Cap-Weighted and the SciBeta Developed Cap-Weighted.

21-Jun-2002 to 31-Dec-2018 (RI/USD)	Standard HFI	Sector Neutral	Narrow HFI HFI	MSCI Min Vol
Panel A - SciBeta USA				
LVol Rel. Ret	-2.35%	-0.87%	-6.16%	-7.08%
HVol Rel. Ret	6.55%	5.05%	7.96%	6.99%
Rel. LVol/HVol Spread	**-8.90%**	**-5.92%**	**-14.12%**	**-14.06%**
Panel B - SciBeta Developed				
LVol Rel. Ret	-1.84%	-0.77%	-4.24%	-7.63%
HVol Rel. Ret	7.26%	5.63%	8.36%	7.95%
Rel. LVol/HVol Spread	**-9.10%**	**-6.40%**	**-12.60%**	**-15.59%**

EXHIBIT 9

Absolute conditional performance based on bull/bear Low Volatility return regimes of SciBeta Defensive offering and MSCI Minimum Volatility on SciBeta USA and SciBeta Developed universes

The analysis is based on daily total returns in USD from 21-Jun-2002 (base date of SciBeta indexes) to 31-Dec-2018. All statistics are annualized. Yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. Bull regimes are defined as months with positive performance of the Low Volatility index. Bear regimes are defined as months with negative performance of the Low Volatility index. Extreme Bull regimes are the top 50% of bull months. Extreme Bear regimes are the bottom 50% of bear months. Coefficients significant at 5% p-value are highlighted in bold. The smart factor indexes used are the SciBeta USA High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy), SciBeta USA High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy) (Sector Neutral), SciBeta USA Narrow High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy), SciBeta Developed High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy), SciBeta Developed High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy) (Sector Neutral) and the SciBeta Developed Narrow High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy). The cap-weighted indexes are the SciBeta USA Cap-Weighted and the SciBeta Developed Cap-Weighted.

21-Jun-2002 to 31-Dec-2018 (RI/USD)	Standard HFI	Sector Neutral	Narrow HFI HFI	MSCI Min Vol
Panel A - SciBeta USA				
Bull Ret	14.83%	10.48%	17.39%	14.13%
Bear Ret	5.16%	10.76%	-0.29%	1.63%
Bull/Bear Spread	9.67%	-0.27%	**17.68%**	12.50%
Panel B - SciBeta Developed				
Bull Ret	13.73%	10.78%	15.70%	13.58%
Bear Ret	5.33%	9.21%	0.91%	-0.32%
Bull/Bear Spread	8.41%	1.58%	**14.79%**	**13.90%**

standard HFI index is again a good compromise, since it provides good level of protection in high volatile market regimes, almost as high as the Narrow HFI index and suffers much smaller relative losses in low volatile markets. Moreover, for the same level of protection in high volatile markets if suffers lower relative losses in low volatile markets than the MSCI index, due to its better factor intensity.

Finally, in Exhibit 9, we show absolute performance of the different indexes conditional on the returns of the Low Volatility factor. We observe that, as expected, the Narrow HFI index has the highest return in bull Low Volatility factor regimes (+17.39% and +15.7% on US and Developed) and very low return compared to all other indexes in bear Low Volatility factor regimes (-0.29% on US and +0.91% Developed). The bull/bear spread return is high, which means that the index is highly conditional on the Low Volatility factor regimes. The standard HFI index has a return of +14.83% in bull Low Volatility factor regimes on US and +13.73% on Developed, which is similar to the MSCI Minimum Volatility index. However, it delivers a return of +5.16% in bear Low Volatility factor regimes on US and +5.33% on Developed, which is much better compared to the MSCI index (+1.63% and -0.32% on US and Developed). The sector neutral HFI index has a very low conditionality to the factor return regimes, since it delivers almost the same returns in both bull and bear Low Volatility factor regimes and exhibits very low conditional spread returns (-0.27% on US and +1.58% on Developed).

As expected, the sector neutral HFI index has a low conditionality to the Low Volatility return regimes because

EXHIBIT 10

Macroeconomic sensitivity of SciBeta Defensive offering and MSCI Minimum Volatility on SciBeta USA and SciBeta Developed universes

The analysis is based on daily total returns in USD from 28-Jun-2002 (base date of SciBeta indexes) to 28-Dec-2018. All statistics are annualized and regressions are based on weekly total returns in USD. The yield differential of Secondary US Treasury Bills (3M) is used as a proxy for the T-Bill Factor. Term Spread factor is the difference in yield differential of 10-year US Treasury Bonds and yield differential of 3-year US Treasury Bonds. The Market factor is the excess return series of the cap-weighted index over the risk-free rate. Credit Spread factor is the difference in yield differential of BAA Corporate bonds and AAA Corporate bonds. Coefficients significant at 5% p-value are highlighted in bold. The smart factor indexes used are the SciBeta USA High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy), SciBeta USA High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy) (Sector Neutral), SciBeta USA Narrow High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy), SciBeta Developed High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy), SciBeta Developed High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy) (Sector Neutral) and the SciBeta Developed Narrow High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy).

21-Jun-2002 to 31-Dec-2018 (RI/USD)	Standard HFI	Sector Neutral	Narrow HFI HFI	MSCI Min Vol
Panel A - SciBeta USA				
Unexplained	**0.00**	**0.00**	**0.00**	0.00
Market Beta	**0.78**	**0.85**	**0.71**	**0.80**
T-Bill	0.05	-0.01	-0.32	**-0.79**
Term Spread	**-1.48**	-0.46	**-1.80**	**-2.13**
Credit Spread	-0.23	-0.09	0.11	0.18
R Sqrd	91.0%	95.1%	84.5%	91.2%
Panel B - SciBeta Developed				
Unexplained	**0.00**	**0.00**	**0.00**	**0.00**
Market Beta	**0.76**	**0.82**	**0.71**	**0.70**
T-Bill	-0.11	-0.08	-0.32	**-0.65**
Term Spread	**-1.29**	**-0.73**	**-1.63**	**-2.39**
Credit Spread	-0.09	0.04	0.26	0.48
R Sqrd	93.5%	96.3%	89.3%	88.1%

of its sector neutrality objective that dilutes its exposures to the factor, unlike the Narrow HFI index, which exhibits the highest conditionality. The standard HFI index is again a good compromise, since it delivers a good performance in bull regimes (similar to the MSCI index) and a positive return in bear regimes, which is much higher relative to the MSCI index. The latter is possible because the standard HFI index has a high factor intensity since it has positive exposures to other rewarded risk factors.

6. Low Sensitivity to Macroeconomic Factors

In this section, we analyze the sensitivity of our defensive indexes to three different macroeconomic indicators:

- T-Bill or short-term rates – which reflects inflation expectations
- Term spread – which reflects monetary policy expectations
- Credit spread – which reflects risk aversion

Defensive strategies tend to overweight defensive sectors, like Utilities. This sector has an exposure to interest rate risks for two main reasons. First, the sector has lower risks than global equities, meaning that in a low interest rates period, as it was the case over the last years (and is still the case currently), bond investors can have interests to invest in Utilities companies, since they provide higher yields than bonds through their high dividend payouts. This is the so-called bond-like feature of the Utilities sector. If bond yields increase, Utilities stocks become less attractive and bond investors sell their investments. This negatively impacts stock prices and therefore returns. Second, utilities companies have high capital expenditures that cannot be solely financed by free cash flows and therefore require debt financing, which is cheaper than equity financing. In a rising rate environment, their interest payments will increase and have a negative impact on their earnings. The latter will have a negative impact on their prices and returns. For these reasons, we can expect negative exposures of defensive solutions to T-Bill and Term spread factors.

Defensive strategies should be positively related to risk aversion and therefore to credit spread, which is a measure of financial distress. Indeed, we should expect spreads between BAA and AAA bonds to increase when market volatility increase. For this reason, we can expect positive exposures of defensive solutions to credit spreads.

We see in Exhibit 10 the different exposures of our defensive indexes on the macroeconomic factors from which we can draw the following conclusions.

The sector neutral HFI index has the lowest exposures to the various macroeconomic factors and especially to interest risk factors because of its sector neutrality objective, which implies weak relative exposures to defensive sectors, like Utilities, that are negatively impacted by interest rate risks. We highlight that its exposure to the Term Spread factor is negative (-0.46 and -0.73 on US and Developed universes respectively), but is lower compared to the other indexes of our offering and much reduced compared to the MSCI Minimum Volatility index. Defensive investors that are worried by a sudden increase in rates should favor this index.

The standard HFI index only significant exposure is to the Term Spread (-1.48 and -1.29 on US and Developed universes respectively). We highlight that while the index offers the same level of volatility reduction and protection in bear markets than the MSCI index, it offers much reduced exposure to macroeconomic factors and much better risk-adjusted performance. Indeed, the MSCI index has strong negative exposures to T-Bills and Term Spread factors. This is due its negative exposures to other rewarded risk factors, which results in a low factor intensity.

The Narrow HFI index has the highest macroeconomic factor exposures of our offering, especially to the Term Spread factor, because it has the strongest exposure to the Low Volatility factor. Nonetheless, while it provides a higher exposure to the Low Volatility factor than the MSCI index, it provides lower macroeconomic exposures, especially to interest rate risks than the latter. This is a confirmation that, when properly constructed, defensive strategies can limit exposures to interest rate risks, through positive exposures to other rewarded risk factors.

7. Conclusion

The design of Scientific Beta's defensive offering answers investors' needs for a reduction in volatility compared to the cap-weighted index and also offers capital protection in bear markets (see Exhibit 11). This is achieved through the Smart Beta 2.0 construction framework, which first selects stocks with low volatility, then applies an HFI filter to remove the stocks with the lowest multi-factor scores and finally diversifies away idiosyncratic risks with a diversified weighting scheme. This approach delivers high factor intensity and good long-term risk-adjusted performance, because it harvests the Low Volatility factor, which is known to provide an additional source of performance than the cap-weighted index over the long-term, while maintaining positive exposures to other rewarded risk factors, thanks to the use of the HFI filter. Moreover, Scientific Beta's top-down approach, gives investors the flexibility to select the solution that fits with their investment objectives by offering them three different versions of defensive indexes.

The High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy) index offers a good exposure to the Low Volatility factor and hence a good level of volatility reduction and protection in bear markets (similar to the popular benchmark – the MSCI Minimum Volatility index), while providing the highest factor intensity as well as the best risk-adjusted performance of our offering. This index is recommended for defensive investors with weak tracking error constraints who are seeking a solution that is not only defensive, but that is also properly exposed to other rewarded risk factors in order to obtain the highest risk-adjusted return.

EXHIBIT 11

Recap of the key elements of our defensive offering

The analysis is based on daily total returns in USD from 28-Jun-2002 (base date of SciBeta indexes) to 28-Dec-2018. All statistics are annualized and regressions are based on weekly total returns in USD. The yield differential of Secondary US Treasury Bills (3M) is used as a proxy for the T-Bill Factor. Term Spread factor is the difference in yield differential of 10-year US Treasury Bonds and yield differential of 3-year US Treasury Bonds. Coefficients significant at 5% p-value are highlighted in bold. The smart factor indexes used are the SciBeta USA High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy), SciBeta USA High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy) (Sector Neutral), SciBeta USA Narrow High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy), SciBeta Developed High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy), SciBeta Developed High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy) (Sector Neutral) and the SciBeta Developed Narrow High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy). The cap-weighted indexes are the SciBeta USA Cap-Weighted and the SciBeta Developed Cap-Weighted.

21-Jun-2002 to 31-Dec-2018 (RI/USD)	Standard HFI	Sector Neutral	Narrow HFI HFI	MSCI Min Vol
Panel A - SciBeta USA				
Volatility Reduction	-21%	-15%	-25%	-17%
Sharpe Ratio Improvement	74%	60%	67%	33%
Protection in Bear Markets	10.8%	7.2%	14.0%	10.4%
Factor Intensity	0.65	0.52	0.65	0.19
Tracking Error	6.0%	4.6%	7.5%	5.2%
Term Spread Exposure	**-1.48**	-0.46	**-1.80**	**-2.13**
Panel B - SciBeta Developed				
Volatility Reduction	-35%	-31%	-39%	-38%
Sharpe Ratio Improvement	96%	77%	96%	56%
Protection in Bear Markets	11.2%	8.5%	14.1%	14.1%
Factor Intensity	0.65	0.56	0.60	0.26
Tracking Error	4.9%	3.9%	5.9%	6.0%
Term Spread Exposure	**-1.29**	**-0.73**	**-1.63**	**-2.39**

The High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy) (Sector Neutral) index offers the lowest volatility reduction and protection in bear markets. Moreover, it delivers the smallest Sharpe ratio of our offering. Nonetheless, its additional objective is also to reduce tracking error through the sector neutrality objective. The objective is achieved, since the index delivers the lowest tracking error and the best information ratio of our offering. Moreover, it has low conditionality to market and macroeconomic factors in particular to T-Bills and Term Spread factors. This index is recommended for defensive investors with tracking error constraints wanting to avoid negative relative performance in bull market regimes or in rallies of some sectors and that are worried by rising interest rates.

The Narrow High Factor Intensity Low Volatility Diversified Multi-Strategy (4-Strategy) index has the highest exposure to the Low Volatility factor and therefore delivers the strongest volatility reduction and offers the best protection in bear markets. The index is therefore designed for investors that seek the most defensive solution. Obviously, this high exposure to the Low Volatility factor comes with a cost, in the form of lower exposures to other rewarded risk factors, higher conditionality to various regimes, meaning important relative losses in bull markets for instance, and high tracking error. Moreover, it has the strongest sensitivity to macroeconomic factors of our offering and in particular to T-Bills and Term Spread factors. For Scientific Beta, this index should not be considered as a standalone solution, but rather as an overlay solution for investors willing to modify their portfolio's market beta or Low Volatility exposure, while simultaneously avoiding a reduction in the factor intensity of their existing portfolio thanks to the HFI filter.

To conclude, Scientific Beta's defensive offering is motivated by a strong belief that investors are not identical and that their investment objectives and constraints are different. This is why we believe that our top-down approach, which is simple and transparent, is the best approach for our clients. Finally, we offer risk control options (such as the sector neutrality objective) and concentrated selections (such as the narrow High Factor Intensity), which allows investors to explicitly define their preferences in terms of relative risks and level of defensiveness, which are often hidden by-products in defensives solutions offered by competitors. Whatever the defensive index chosen, the fact that they are part of the Scientific Beta smart factor indexes ensures that they benefit from the same features as all the other indexes we offer, namely the good diversification of unrewarded risks and the capacity to limit undesired risks. For investors, this is the guarantee that their choice will be the best possible. •

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What are the Risks of Making Changes to Indexes?

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- **Methodologies of factor-based equity indexes undergo frequent changes, leading to inconsistencies over time.**
- **Inconsistencies in index methodology make it difficult for investors to evaluate index offerings and may expose them to a risk of relying on spurious performance records.**
- **Lack of transparency about methodology changes exacerbates data-mining risks.**
- **Providers of factor products should be consistent in their investment principles and transparent about the methodological changes they make.**

1. Introduction

Investors' interest in smart beta strategies has grown tremendously over the past decade. That investors have often been disillusioned by the performance after fees delivered by active management has been a key driver of this development. The use of systematic factor index strategies is seen as more transparent, and offering more consistent exposure over time compared to the discretionary decisions of an active manager. However, while indexes apply a systematic set of rules at any point in time, index rules do change over time. This is true for both cap-weighted market indexes and smart beta indexes. For investors who are looking for a strategy with high consistency over time, time variation in index rules is an issue that merits scrutiny.

In fact, a risk of time-varying index rules is that smart beta index providers could develop an odd resemblance to active management providers. Similar to active fund providers launching new funds when existing funds underperform, new indexes with attractive backtests could be launched to replace the bad live track records of existing indexes. However, there are also legitimate motives for changing an index methodology over time. For example, new rules may improve the ease of implementation. Just like methodologies for cap-weighted indexes introduced a free-float adjustment to improve liquidity, smart beta index methodologies may change their rules to improve investability. Moreover, just like cap-weighted index rules may reconsider how to categorize countries into emerging and developed markets, smart beta index rules could be updated to improve the implementation of a given factor strategy.

However, it is important that the changes are consistent with investment objectives. For example, it would be surprising if a multi-factor index suddenly targets a different set of factors than it did in the past. Index providers should have a sound justification for why index methodology changes align with their investment philosophy.

Another crucial aspect when there is a change in index methodology is transparency. In a recent survey of European ETF investors, Goltz and Le Sourd (2018) find that one of the key challenges that investors face when analyzing factor-based strategies is difficulty in accessing information, in particular for risks such as data-mining risks. Changes to index rules and the performance characteristics of older index offerings should be transparent to allow investors to evaluate a provider's strategies.

This article analyzes the implications of inconsistencies for investors, and illustrates problems with industry practice using examples from recent index changes.

2. What do inconsistencies over time mean for investors?

2.1. Data-mining risks

The key issue arising from inconsistency over time of index methodologies is a data-mining risk. Frequent changes of index methodologies add an important layer of flexibility to providers, thus increasing the risk of data snooping.

For example, one of the most common methodology changes in the industry is "enhancing" factor definitions. Searching over many possible "enhanced factors", it is easy to find a definition that shows stellar back-tested performance purely by chance. Harvey and Liu (2016) refer to such factors as "lucky factors". Besides finding the "best" variable as a proxy, there are a number of adjustments that smart beta index providers use, such as sector and/or country relative-scoring, transformation of a factor score distribution (logarithmic, normal, etc.), aggregating multiple variables into composite scores using arbitrary weights, to name only a few options. The more flexibility, the higher the selection bias.

When assessing the live performance of an index, it will always be possible to identify a better-performing factor definition for the relevant time period. If providers replace factor definitions because one of many backtested "enhancement" options outperforms the live index performance, investors will not reap any benefits as the improvement will be spurious. Moreover, if providers follow such a data-mining approach, backtests of newly launched indexes would indicate performance that is artificially inflated.

There is a more fundamental reason why frequent changes in factor definitions are problematic. Such changes would suggest that these factors are not the persistent drivers of returns that investors are looking for. Factors such as value and momentum are precisely recognized as persistent factors because they deliver premia that are justified economically, and factor premia have been documented empirically, including for the 30-year period after the initial results were made publicly available (see McLean and Pontiff (2016)). Factors that require frequent updating cannot be persistent factors and thus frequent updating is a sign of a lack of robustness.

Enhancing factor definitions is just one example of possible methodology changes. The data-mining critique applies not only to the definition of a particular factor, but also to the selection of factors. Simply choosing the factor combination with the "best" in-sample performance will not lead to robust performance in the future. Selection and weighting of different factors should be well-justified, not purely backward looking.

Another pitfall of methodological inconsistencies is model-mining risk. In fact, even if the factor definition and factor selection remain fixed, multi-factor indexes may rely on different portfolio construction models to combine factor exposures into an index. When deciding on portfolio construction, a multitude of options is again available to providers. In particular, portfolio construction could be subject to arbitrary constraints. For example, one index provider reports how different levels of constraints were tested over the backtest and how the selected constraints produced the multi-factor index with the highest information ratio[19]. Using a large number of ad-hoc constraints (sector/country weights, security weights, factor exposures, turnover) in portfolio construction exacerbates model risk. The risk is that one may pick the constrained model that works well in the back-tests but does not produce robust performance out-of-sample. Again, frequent and unjustified changes in methodologies would allow providers to replace a model that has done poorly in a live track record with a model that has achieved better results in the backtest.

For investors, it is crucial to identify whether index changes are purely motivated by opportunities for backtest enhancement, or whether providers are actually offering an improvement to an existing index. Andrew W. Lo argued in the early 1990s that reducing data-snooping risk requires some framework to limit the number of possibilities in the search process.[20] Indeed, one of the fundamental principles to avoid data-mining risk is to limit the range of possible options a provider could implement as index changes. With less flexibility to the provider, there will be less risk of data mining. To put a constraint on the amount of flexibility providers have, investors can require that any methodology change remains consistent with the investment principles of the existing offerings. Indeed, if changes are conducted within an explicit methodological framework and with reference to a clear investment philosophy, there is little room for data mining. Requiring a consistent framework and investment philosophy is one of the best weapons against spurious performance records. Such a framework is nothing but the realization of investment discipline.

2.2. Conflict with long-term investing

Beyond data-mining risks, inconsistency over time is a general problem when making decisions about long-term investments. The majority of institutional investors, such as pension funds, have a long-term investment horizon,

[19] Source: Exhibit 17 in The MSCI Diversified Multi-Factor Indexes - Maximizing Factor Exposure While Controlling Volatility, Research Insight, MSCI, May 2015
[20] https://www.hillsdaleinv.com/uploads/Data-Snooping_Biases_in_Financial_Analysis%2C_Andrew_W._Lo.pdf

implied by the nature of their liabilities. Maintaining a long-term horizon is among the most frequently referred to investment principles of pension funds and sovereign wealth funds[21].

Short-term and ad-hoc adjustments of investment methodologies are at odds with effective long-term investing. Instead, long-term investing requires deciding on investment principles and staying the course in the long term. Recommendations for governance principles of pension funds argue that "investment beliefs can help investors steer a consistent course, regardless of today's investment fads" (Lydenberg 2011). Appropriate index strategies should reflect this focus on consistent principles and not change methodologies according to the latest fad. Moreover, there is evidence that when investors change their exposures frequently over time, these efforts typically have adverse results (see Frazzini and Lamont (2008)). Compared to staying the course, such frequent changes compromise investment results.

More specifically, it appears that erratic factor index methodologies are at odds with the foundations of factor investing. For example, consider the position of an investor who blindly follows frequent changes to a provider's factor definitions and factor menu. If investors really believe that the factors they are using to invest change very frequently over time, controlling their current exposure to such factors is close to useless as a support for investment decisions, as these should rely on factors that will still be relevant drivers of performance in the future. Indeed, the academic evidence on factor investing suggests that factors are rewarded over the long-term. Index methodologies that frequently change factor definitions, or that change the set of factors at different points in time, are inconsistent with the principles of factor investing.

3. Which inconsistencies exist in the industry?

This section discusses in detail the three most common changes in the methodology of factor indexes, namely factor selection, factor definitions, and investment principles. The following sub-sections also provide examples of recent index changes.

3.1. Changing factor selection

Extensive empirical research over the past decades discovered hundreds of "rewarded" factors, also known as the "factor zoo". However, there are only a few consensual factors that survived academic scrutiny. The set of factors that appears in consensual models of expected return is not only relatively small, but also very stable over time. For example, Fama and French proposed a three factor model in 1993 and extended the set of factors to five in 2015. In a span of more than two decades, two factors were added to the menu while maintaining the factor definitions of the initial factors. Moreover, the new factors follow the same construction methodology as the existing ones. Change is not more frequent simply because newly proposed empirical asset pricing factors need to pass a high hurdle before they are accepted as consensual factors. While there are hundreds of factors in the "factor zoo", only a handful have been confirmed by independent replication, post-publication evidence and rigorous theoretical models. A high hurdle for acceptance of factors implies that the relevant set is relatively stable over time.

If one sets a low hurdle on accepting new factors, we would expect to see a much faster pace of change. The flipside would be that such a low hurdle will increase the risk for accepting spurious factors that have not undergone a sufficient amount of scrutiny. New sets of factors could appear frequently depending on "factor fads". Likewise, well-established factors could be abandoned prematurely, without sufficient validation and replication of results.

When considering the factor selection in multi-factor flagship products, we observe a fast pace of change over time. For example, in 2013, MSCI launched a series of Quality-Mix indexes, representing a flagship multi-factor offering. The index targeted balanced exposures to Value, Low Volatility and Quality factors. However, MSCI decided to exclude the Low Volatility factor from their new flagship offering in 2015, namely the Diversified Multiple-Factor series. The new index targets Value, Quality, Size and Momentum factors[22].

The exclusion of the Low Volatility factor does not appear to be guided by the consideration that it is not a true rewarded factor[23]. A relevant question is whether the exclusion of this factor in the new multi-factor index (Diversified Multiple-Factor Index series, or DMF), allowed the information ratio to be improved in the back-test as of the launch date.[24] One may ask what would have happened to the back-tested performance of the DMF indexes if MSCI had instead included the Low Volatility factor in the computation of the composite score used in the DMF optimizer. In fact, MSCI reports the results for various selections of factors in the publication introducing the DMF. There we learn that including the Low Volatility factor would have caused a deterioration of the information ratio from 1.14 to 0.86 for the world index over the 16-year back-test period[25]). Naturally, selecting rewarded factors on the basis of their performance over a back-test period is backward-looking and can prove counter-productive out-of-sample. We will return to the question of performance since launch of the index in section 3.4 below.

Inconsistencies regarding factor selection might exist not only with the previously released product offerings, but also with the previous research findings. For example, the launch of the RAFI multi-factor index series was backed up by a research publication, which explicitly emphasized the robustness of factors it included, such as quality and size (see e.g. Arnott, Beck and Kalesnik (2016)). However, an earlier publication (see Beck et al. (2016)) concluded that the quality and size factors are not robust. More specifically, we can compare the following two statements[26]:

- From September 2016: "We found that two of the more popular factors—quality and size—lack robust empirical evidence to support them."[27]
- From January 2017: "RAFI Multi-Factor is designed to offer the following benefits: Combines theoretically sound and empirically robust single-factor strategies—value, low volatility, quality, momentum and size…"[28]

Ultimately, such examples show that provider views on what a robust factor is may change dynamically over time, sometimes within very short time periods. Such short-term variations in fundamental beliefs about factors appears to be inconsistent with the idea that factor indexes should represent strategic choices for long term investing.

Indeed, one provider states about its factor investing framework that[29]: "Factors or factor groups may be added, modified or removed, […] to insure it accurately reflects a set of robust factors and factor groups at a given point in time". The irony of relabeling spurious factors as "robust at a given point in time" reflects to what extent robustness is neglected in current industry practices.

The problem with inconsistency over time in the factor set is that such changes have a tremendous impact on backtest performance. We provide a stylized example to illustrate the impact of selecting different sets of factors. First, let us consider the historical performance of portfolios that allocate equal weights to at least three factors out of six. Table 1 shows the distribution of Sharpe ratios of forty-two possible portfolios that can be formed with different factor selections. The results indicate that the risk-adjusted performance of multi-factor indexes varied between 0.51 and 0.73 over the forty-year period, a range of 0.22 between the highest and lowest Sharpe ratio. If we look at the ten-year sub-periods (a more typical length for a backtest period), the performance range, i.e. the difference between the highest and lowest Sharpe ratios, may be as high as 0.42. This example suggests that selecting factors differently in a new index offers sufficient flexibility to show large improvements in backtested performance relative to an existing index.

The performance differences become even more pronounced when considering relative performance. The second panel of Table 1 reports the information ratios of stylized portfolios. Over the full sample, the information ratios range from 0.11 to 0.81. The dispersion is even higher when looking at shorter periods of ten years. Overall, the analysis indicates that factor selection in multi-factor indexes has a dramatic impact on the performance, both in absolute and relative terms, especially when looking at short backtest periods.

[21] For example, the Environment Agency Pension Fund states that "applying long-term thinking to deliver long-term sustainable returns" and "applying robust approach to effective stewardship" are one of its main investment principles. See: https://www.eapf.org.uk/investments/responsible-investment
The British Columbia Investment Management Corporation states that their primary responsibility is to "ensure enduring long-term investment returns". See: http://www.bcimc.com/ResponsibleInvesting/Approach.asp
[22] Regarding the launch of the MSCI Quality Mix Index series, please refer to: https://www.businesswire.com/news/home/20130805005345/en/MSCI-Launches-New-Quality-Mix-Indices
Regarding the launch of For MSCI Diversified Multi-Factor Indexes, refer to:
https://www.businesswire.com/news/home/20150319005267/en/MSCI-Introduces-Diversified-Multi-Factor-Indexes
[23] In the following document, MSCI argues that Low Risk factor is a rewarded factor: Foundations of Factor Investing, Research Insight, MSCI, December 2013.
[24] In the aforementioned May 2015 document, MSCI justify dropping Low Risk because "the aim was to deliver market-like variance and beta" and "by definition the inclusion of low volatility would result in below-market risk." One may object that this is a simplistic statement and that it is possible to include a Low Risk dimension in a multi-factor product while maintaining a neutral risk profile. In any case, the reason provided is not very convincing since the optimizer is in fact free to disregard market volatility under certain circumstances and the back-test shows that the product has displayed a beta well below market for prolonged periods of time (refer to that document's Exhibit 12). While the definition of low volatility that was tested by MSCI has not been disclosed, it seems to have produced undesirable results with the composite scoring security-level optimization algorithm used by MSCI.
[25] See Exhibit 16 in the aforementioned May 2015 document. This deterioration is caused by a jump in the tracking error that is not compensated by the rise in relative performance: the former shoots up 41.5% (from 4.1% to 5.8%) when Low Volatility is included, while the latter only grows by 8.7% (moving from 4.6% to 5%).
[26] Emphasis added
[27] See https://www.researchaffiliates.com/en_us/publications/journal-papers/312_will_your_factor_deliver_an_examination_of_factor_robustness_and_implementation_costs_factor_zoology.html
[28] https://www.researchaffiliates.com/en_us/strategies/rafi/rafi-multi-factor.html
[29] Introducing MSCI FaCS, January 2018.

TABLE 1

Distribution of performance numbers for different factor selections

The table reports distribution of Sharpe ratios and Information Ratios of 42 portfolios, each of them corresponding to different factor selections. The asset returns are synthetic multi-factor portfolios constructed as a sum of market return plus equal-weighted returns of long-short equity factors, where we make all possible factor selections (at least 3 out of 6).

Time Period	Min	5th Percentile	Median	95th Percentile	Max	Range (Max-Min)
Distribution of Sharpe Ratios						
1978-1987	0.47	0.50	0.60	0.70	0.74	0.27
1988-1997	1.05	1.08	1.17	1.27	1.30	0.24
1998-2007	0.29	0.34	0.44	0.53	0.56	0.27
2008-2017	0.34	0.42	0.54	0.67	0.76	0.42
1978-2017	0.51	0.54	0.64	0.71	0.73	0.21
Distribution of Information Ratios						
1978-1987	0.27	0.36	0.83	1.31	1.52	1.25
1988-1997	-0.34	-0.18	0.25	1.06	1.26	1.59
1998-2007	0.20	0.22	0.53	0.89	0.95	0.75
2008-2017	-0.24	-0.04	0.20	0.55	0.75	0.99
1978-2017	0.11	0.23	0.42	0.69	0.81	0.69

TABLE 2

Selecting "the best" factor combination based on back-tests

The table reports the performance of active strategies. All the strategies are synthetic portfolios that correspond to the sum of market returns and equal-weighted returns of different long-short factors. The factor selection is done on the basis of historical performance (calibration period). The combination of factors that has the highest return over the calibration period is held for different time periods (HP in years). The out-of-sample degradation is the difference between relative returns of the strategies during the holding and calibration periods. The reported numbers are the average of those differences across all holding periods in the sample. The returns are relative to the six-factor equally weighted portfolio. The performance measures are computed over the period 1/7/1980 – 31/12/2017.

Selecting past winner	6F EW	Calibration period = 5 year			Calibration period = 10 year		
		H=1	H=2	H=3	H=1	H=2	H=3
Sharpe Ratio	0.68	0.58	0.55	0.59	0.57	0.59	0.60
Information Ratio	0.54	0.44	0.35	0.53	0.37	0.41	0.40
Out-of-sample degradation of returns, relative to 6F EW	**-**	**-3.0%**	**-4.2%**	**-3.8%**	**-3.0%**	**-3.0%**	**-3.1%**

Thus far, we have only analyzed in-sample performance of portfolios that tilt towards different sets of factors. It is more relevant to analyze what happens when one periodically selects a factor combination with the most attractive backtest. In the following exercise, we pick factor combinations based on the returns over the past five and ten years of data. Again, we limit the minimum number of factors to three. After formation, the selected multi-factor index is held for different horizons (HP).

The analysis in Table 2 shows that the factor-picking strategies underperform the six-factor equally weighted allocation. More importantly, we find that all of the factor-picking strategies experience degradation in terms of out-of-sample performance. Out-of-sample degradation is the difference in the annualized "value-add" of picking factors between the holding period and the calibration period[30]. For example, selecting factor combinations each year based on the previous five years will result in degradation of annualized relative returns by 3% out-of-sample. The degradation is consistent across different factor picking strategies, regardless of the calibration and holding parameters.

The analysis clearly suggests that factor picking inflates backtest results. We also emphasize that we constructed a relatively well-behaved exercise, with a limited amount of picking across a fixed set of six factors. In practice, index providers could generate much more flexibility by extending the set of factors or flexibly defining weights given to each factor[31]. Given the large amount of flexibility and the pronounced risk of overstated backtest performance, investors should analyze closely what the justification for changes in factor selection is.

3.2. Changing factor definitions

As mentioned above, not only the set of factors, but also the factor definitions underlying the empirical and theoretical evidence on factor investing are very stable over time. Again, there is a stark contrast when it comes to factor definitions used by index providers. In fact, providers tend to update factor definitions frequently. We can provide two straightforward illustrations of changes in factor definitions for different indexes with a value investing orientation.

A first example is the value factor definition used by MSCI, a provider of indexes and analytics tools. Table 3

30 The reported numbers are average across all the holding periods in our sample, and the returns used are relative to the six-factor portfolio to measure the "value" added by actively picking factors.

31 Also note that the previous examples were based on synthetic portfolios, created using market index and long/short equity factors. More specifically, they correspond to portfolios that have equivalent (and constant over the time) exposures to the desired factor combination. Therefore, observed differences in performance should be solely attributed to the factor selection. If additional changes are applied to the index methodology, such as enhancing factor definitions, it will likely lead to more pronounced differences.

TABLE 3

Definitions of Value factor by MSCI across time

Definitions of Value Factor by MSCI	Value 1997	Value-Weighted 2010	Enhanced-Weighted 2014	Value in MSCI FaCS 2018
Variables	- Price-to-Book - Price-to-Forward Earnings - Dividend Yield	- Sales - Book Value - Historical Earnings - Historical Cash Earnings	- Price-to-Book - Price-to-Forward Earnings - Enterprise Value-to-Cash Flows	- Price-to-Book - Earnings Yield - Long-Term Reversals
Weights	Equal weights	Equal weights	Equal weights	- 30% - 60% - 10%
Sector relative scoring	X	X	✓	X

shows the evolution of factor definitions across time for the Value factor used by MSCI[32]. Interestingly, modifications in the Value factor definition concerns not only the variables that form the composite Value score, but also how they are combined, and which adjustments are carried out (such as sector relative scoring). The resulting Value factor definition is a specific choice among a large number of possible variations.

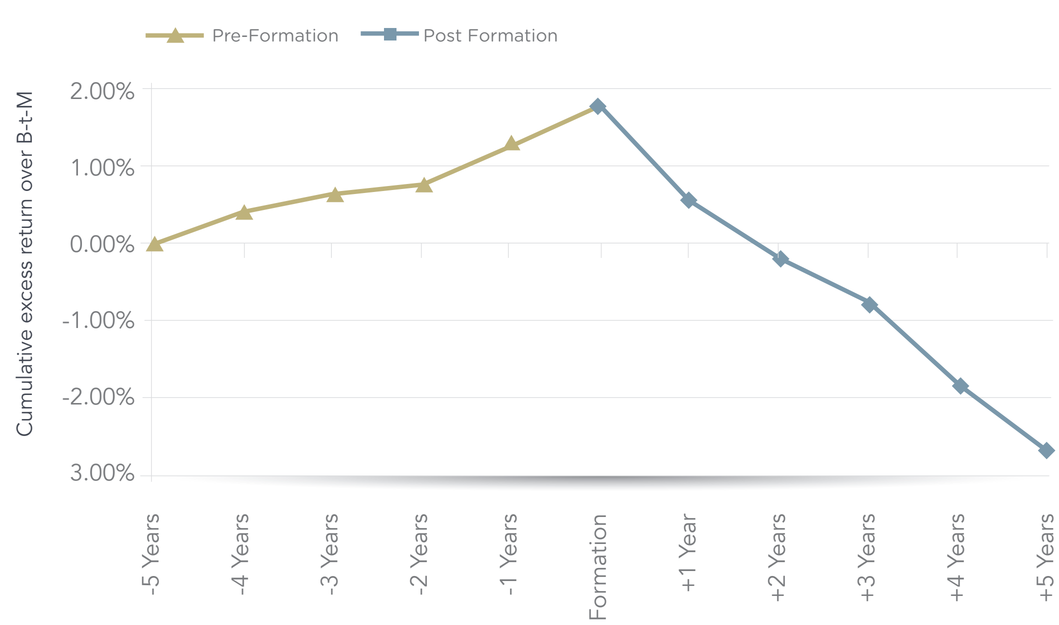
When it comes to the selected variables, we can see that the only consistent variable is the price-to-book ratio, which is indeed the standard characteristic used to capture the Value factor in academic research. The other variables change dynamically over time. For example, "Enterprise Value to Cash Flow" is introduced newly in 2014, but then disappears from the definition favored in 2018. One may ask what the value of such transient variables is. When it comes to adjustments, we observe the same erratic behavior. For example, a sector adjustment was introduced as an "enhancement" in 2014 but is absent from the definition favored in 2018. One could ask why the so-called "enhancement" did not carry through to the definition developed later.

A second illustration of a change in definition of variables are index methodologies for fundamentally-weighted indexes[33]. In 2005, FTSE launched the FTSE RAFI Index series. The latter weighted stocks based on stock-level composite scores made of companies' sales, cash flows, book value and dividends. In 2011, another series of fundamentally-weighted indexes was launched, which is now known as the Russell RAFI indexes. While there are no differences in index objective or conceptual underpinnings between the two index series, the accounting variables to measure the firms' fundamental values are different. More specifically, the Russell RAFI Index series relies on sales, cash-flows and dividends. Unlike the FTSE RAFI index, it excludes the book value. Furthermore, the new index adjusts sales by financial leverage, and adds buybacks to the dividends. It is worth noting that the earlier index that was released in 2005, a few years before the global financial crisis, did not adjust any of the fundamentals for

FIGURE 1

Comparison of cumulative relative returns of the average best in-sample alternative Value strategy with respect to a portfolio based on Book-to-Market.

Source: Amenc et al. (2018). The plot shows cumulative excess returns of ten annually-rebalanced cap-weighted Value-tilted strategies with 50% stock selection out of the universe of 500 US stocks based on ten alternative Value strategies, with respect to a similarly constructed portfolio based on Book-to-Market. Between 1984 and 2009, a five-year formation period is used to pick the best portfolio based on alternative Value definitions and this portfolio is held for another five years. This is done every year for a total of 26 event studies. The chart plots the average outperformance pre- and post-formation with respect to the Book-to-Market portfolio. The alternative Value definitions are Earnings-to-Price, Cash-flow-to-Price, Sales-to-Price, Dividend-to-Price and Payout-to-Price, both plain-vanilla and sector neutral versions for each. The graph is smoothed by using yearly values.



[32] The methodology of MSCI Value (1997) can be found here: https://www.msci.com/eqb/methodology/meth_docs/MSCI_Dec07_GIMIVGMethod.pdf
The methodology of MSCI Value-Weighted(2010) can be found here:
https://www.msci.com/eqb/methodology/meth_docs/MSCI_Value_Weighted_Index_Methodology_Book_Aug2012.pdf
The methodology of MSCI Enhanced Value (2014) can be found here: https://www.msci.com/eqb/methodology/meth_docs/MSCI_Enhanced_Value_Indexes_Methodology_Book_May2015.pdf
The definition of value factor in MSCI FaCS (2018) can be found here:
https://www.msci.com/documents/10199/d923cc18-6493-4245-9707-56e9b6609528
[33] Information about the launch of Russell RAFI index series could be found here: https://etfdb.com/2011/russell-rafi-team-up-on-fundamental-indexes/
The methodology for FTSE RAFI Index series could be found here: https://www.ftse.com/products/downloads/FTSE_RAFI_Index_Series_Rules.pdf?769
The methodology for Russell RAFI index series could be found here:
https://www.ftse.com/products/downloads/Russell_RAFI_Index_Series_Construction_and_Methodology.pdf?805

leverage while the index that was launched in 2011 after the global financial crisis, did include an adjustment for leverage to avoid overweighting highly-leveraged firms. This suggests that the view on how to define basic firm fundamentals has evolved dynamically before and after the financial crisis. Moreover, it has been shown that decisions on leverage adjustments had a tremendous impact on the performance of fundamentally-weighted indexes during the financial crisis with a return difference of 9% in the calendar year of 2008 for fundamentally-weighted portfolios using different rules for leverage adjustments (see Amenc et al. (2015), exhibit 2).

An important question for investors is what the impact of frequent changes in factor definitions is on index performance and on the amount of data-mining risks investors are taking. We now turn to a stylized example where we analyze alternative definitions of the Value factor. Using a five-year formation window, we select the best performing variable based on its in-sample performance. Our set of variables are commonly used as proxies for the Value factor. These are the earnings-to-price, cashflows-to-price, sales-to-price, dividend-to-price and payout-to-price, both plain-vanilla and sector-neutral versions for each.

Once the Value index formation is done, we hold the strategy for five years to get an idea for the out-of-sample performance of the in-sample factor choice. We compare the cumulative returns of the "enhanced" value portfolio to the portfolio based on the standard measure used in the literature, the Book-to-Market ratio. We do this every year between 1984 and 2009 and analyze average results.

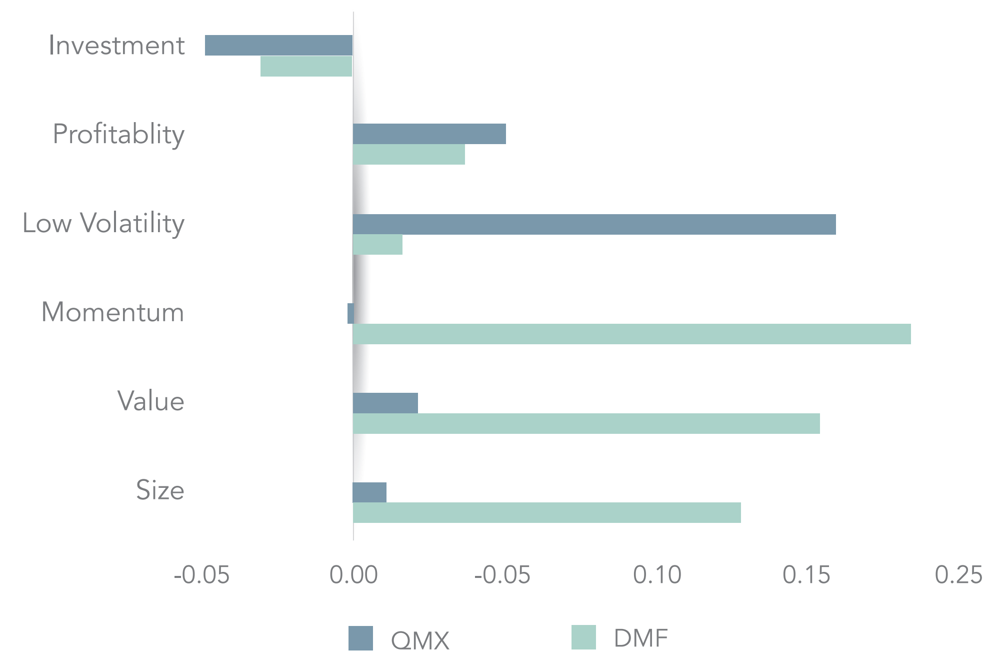
Figure 1 shows the average cumulative relative returns of the best-performing alternative Value definition with respect to Book-to-Market, both pre and post-formation. As the chart below clearly shows, selecting the in-sample "winner" ultimately underperforms the Book-to-Market and drives the cumulative relative returns way below zero. Picking the past winner yields cumulative outperformance over book-to-market of +1.79% in-sample. However, over the following five years, having picked the in-sample winner leads to cumulative underperformance of -2.72%. The fact that the enhanced definitions ultimately underperform the consensual book-to-market factor may be a reason for concern. However, what is most striking about this illustration is that the out-of-sample performance turns out to be about 4.5% below the in-sample performance. Thus, a reported backtest for such a strategy would have over-reported performance by a substantial amount. Indeed, the key risk of fishing for enhanced factor definitions in a backtest is that backtest performance numbers will be inflated relative to what investors can reasonably expect going forward.

We can ask how relevant such a stylized example is for evaluating the risk of overstated backtests that arises in practice. We would argue that data-mining risks in practice are even greater than in our stylized example. In fact, our example is based on picking a single factor definition. In factor definitions used in the industry, we commonly see combinations of multiple variables. Novy-Marx (2015) argues that the use of composite variables in designing and testing factor-based strategies increases the data-mining risks exponentially, due to a "particular pernicious form of data-snooping bias"[34] in composite variable definitions.

FIGURE 2

Factor exposures of MSCI Multi-Factor Offerings

The plot shows cumulative excess returns of ten annually-rebalanced cap-weighted Value-tilted strategies with 50%analysis is based on weekly returns in USD, from 21-Jun-2002 to 31-Dec-2018. Factor exposures are estimated using a seven-factor model, which includes the Market, Size, Value, Momentum, Volatility, Profitability and Investment factors. The market factor is the return of MSCI World minus the return of 3-month US Treasury bills. The remaining are long/short factors that equal-weight the stocks within the highest and the lowest 30% of stocks ranked by the given criterion. Both long and short legs are adjusted to have ex-post market beta of 1, in order to achieve market-neutrality of factors. The adjustment is done ex-post, over the calendar quarters.



3.3. Changing portfolio construction principles

Our illustrations above show that index methodologies may display severe inconsistencies over time in terms of factor selection choices and factor definitions. However, it turns out that the latter two are not the only sources of inconsistency. The portfolio construction principles of smart beta products also change dramatically over time.

One of the most evident examples in recent years is the increased popularity of so-called "bottom-up" approaches in multi-factor investing. The bottom-up approach builds a multi-factor portfolio in a single pass by choosing and/or weighting securities by a composite measure of multi-factor exposures, as opposed to a more traditional top-down approach that assembles multi-factor portfolios by combining distinct sleeves for each factor.

While both approaches aim to capture premia associated with multiple factors, there are significant differences between the two. In particular, bottom-up and top-down portfolio construction rely on a different set of investment beliefs and investment objectives, as shown in Amenc et al. (2017, 2018). Bottom-up approaches try to increase the overall factor exposure, accounting for fine-grain differences in composite exposures. The underlying investment belief is often an assumption that there is a deterministic link between factor exposures and stock returns. In contrast, top-down approaches prioritize portfolio diversification over precision in engineering factor exposures. The underlying investment belief is that expected returns at the stock level are highly noisy and the relation between factor exposures and returns can only be expected to hold in a broad sense.

Of course, investors may expect that the fundamental investment beliefs about factor investing of a given provider do not change frequently over time. As we pointed out above, investment beliefs are necessary for long-term investing, to ground investment decisions in sound principles and avoid being exposed to investment fads. An abrupt change in positioning with respect to bottom-up or top-down portfolio construction thus appears to be inconsistent with sound long-term investing.

However, index providers have displayed a large degree of flexibility on investment beliefs concerning bottom-up and top-down portfolio construction. One example is the adoption of a bottom-up portfolio construction by index provider MSCI, who, on the occasion of the release of a new series of Diversified Multiple Factor indexes, promoted, with its research publications, an approach that was strictly opposed to the top-down approach that the same research teams had supported as part of the launch of the Quality Mix indexes.

A fundamental question for investors is how different the performance of index offerings can be when using flexibility on factor selection, factor definitions, and portfolio construction to come up with new index methodologies. We analyze this question with the following illustration.

3.4. What is the impact of index changes on performance?

We have shown above that frequent changes to different dimensions of factor indexes are quite common in the industry. We also provided stylized examples to show potential consequences for investors. These illustrations isolated the effect on performance from a specific part of the methodology, such as factor selection. We now show an example of changes in index methodology across multiple dimensions.

More specifically, we consider the multi-factor offerings of index provider MSCI, and their evolution in 2015 [35]. The MSCI Quality mix index was the flagship multi-factor index offering prior to 2015. The series targeted the Value, Low Volatility and Quality factors by blending the single-factor indexes in a top-down manner. The new flagship offering, namely the Diversified Multiple-Factor index series, targets the Value, Quality, Momentum and Size factors by running an optimization algorithm to maximize the average factor exposure (bottom-up approach). Factor definitions also differed across the two series, as

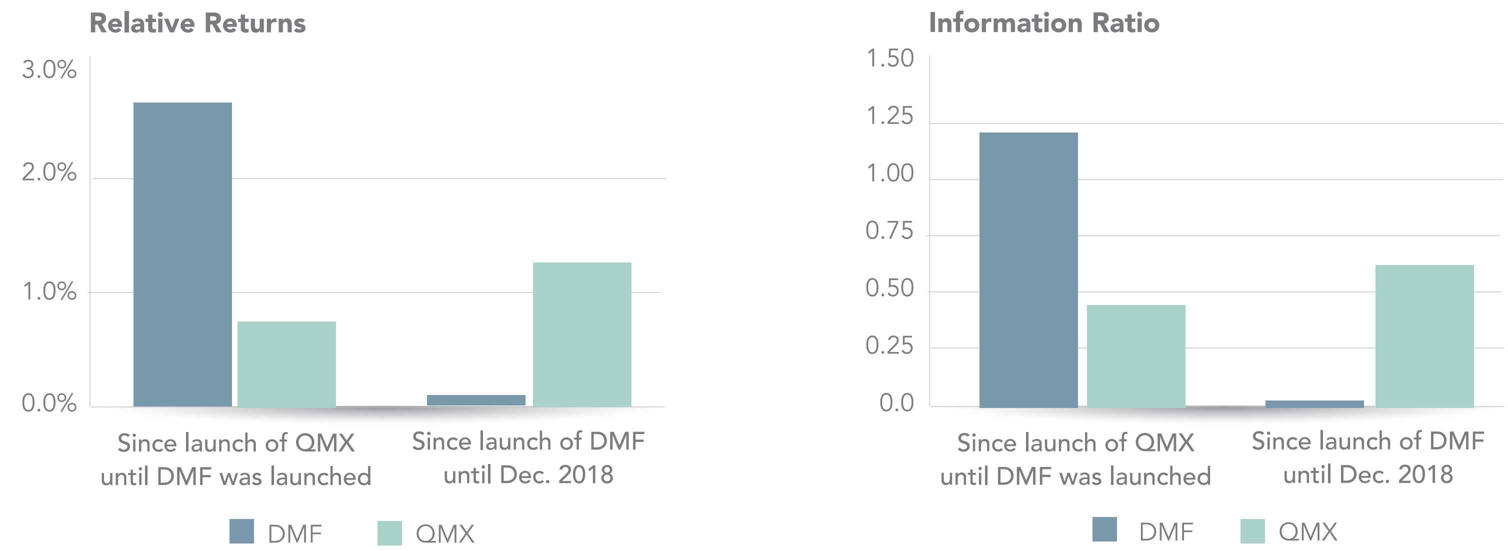
34 Examples for such strategies cited by Novy-Marx (2015) are the MSCI Quality Index, which draws on a composite of three variables, and Research Affiliate's Fundamental Indexes, which rely on composite measures of fundamental firm size.

35 For the methodology of the two multi-factor offerings, please refer to the previous footnotes.

FIGURE 3

Back-test vs. live performance: case of MSCI flagship offerings

The MSCI Quality Mix index series (QMX) was launched on 5-August-2013. The MSCI Diversified Multiple-Factor Index series (DMF) was launched on 19-March-2015. MSCI World has been used as a benchmark.



emphasized in section 3.2. Thus, the new factor index deviated from the older factor index in multiple dimensions.

It is interesting to analyze how these differences in index construction translate into differences in terms of factor exposures. Figure 2 shows the factor exposures of the two strategies. It is obvious from the analysis that the factor exposures of the indexes are extremely different. The MSCI Quality Mix (QMX) is highly exposed to the Profitability and Low Volatility factors, while DMF loads more heavily on the Size, Value and Momentum factors. Changes in factor selection, factor definitions, and in the portfolio construction methodology indeed translate into very different outcomes.

In addition to factor exposures, it is interesting to consider differences in performance. In particular, one might ask whether the performance of the new index appeared significantly better than that of the old index as of the launch date of the new index. Indeed, we find that the new index (DMF) came with a backtest that showed substantially higher returns than the old index, as of the launch date of the new index. At the launch of the new index, its relative returns over the cap-weighted index were 2.7% in the backtest, for the time period since launch of the old index. At that time, the old index (QMX) posted a 0.7% relative return since its launch. In terms of information ratio, the new index more than doubles the performance compared to the old index. After the launch of the new index however, the hierarchy between the two indexes changed. The new index (DMF) has barely been able to beat the benchmark since its release in 2015, while the old index (QMX) outperformed the cap-weighted MSCI World by 1.3%. The old index produced an information ratio of 0.63 compared to an information ratio of 0.01 for the new index (DMF). Figure 3 provides an overview of these results.

While we understand the motivation for index providers to launch a new series of indexes that is very different from the first one when their investment beliefs do not appear to lead to good performance, these new investment beliefs, often formed from concerns over in-sample performance, do not necessarily hold up against out-of-sample robustness tests.

Indeed, choices made by product providers are often guided by backtested performance. For example, one of the index providers explicitly mentions that "factors are selected on the basis of the most significant t-stat values[36]. Another provider states that during the search of factor definitions, "adjustments could stem from examining factor volatilities, t-stats, Information Ratios", with an "emphasis on factor returns and information ratios"[37]. Such statements suggest that investors indeed need to be wary of data-mining risks.

The performance patterns above at least confirm the common disclaimer that past performance is not a guarantee of future results. More precisely, backtests of new index methodologies that look better than the live performance of existing indexes are not a guarantee of actual improvement.

4. Managing index changes: how to achieve transparency for investors

While frequent changes to index methodologies do entail risks, it also seems inevitable that methodologies change as markets and the investment industry evolve, and research comes up with new approaches that offer better ways to achieve investment objectives. We have argued above that it is important that those changes are consistent with investment principles. Investors should require a sound rationale for an index change to make sure that a new index is justified by reasons other than an embellished backtest.

Moreover, changes in index methodology or index offerings should be transparent to allow investors to assess both the reasons for and the implications of methodological changes. In particular, investors should have access to the performance of previous offerings. For example, if a product provider updates the rules of an existing index, the performance record of the index before the change was effective will still be available. This is common practice for example when a new country is added to the universe of a cap-weighted index. Another possibility is to launch a new index while maintaining the production of the previous offering(s), hence allowing investors to make comparisons between older indexes and newer indexes.

In both cases, the question of information on these changes is important. It is the only thing that allows investors to be able to understand the changes made and to follow the live track records of the indexes, as they can do with managers when they are interested in the ability to generate outperformance, which is also the promise of smart beta indexes.

It should be recognized that the level of transparency between index providers is fairly variable. For example, in the case of the indexes considered in the illustration in section 3.4, there is transparency in the sense that MSCI has kept publishing the performance of its old flagship offering (QMX) after launching the new multi-factor indexes (DMF) in 2015, and presents these two indexes as being part of its standard multi-factor index offering. We can regret the confusion of the concepts and the competition (inconsistency) between the investment beliefs of research teams from the same company, but at least it is easy for the investor to find the information. From that perspective, MSCI respects the transparency and governance rules of its range of indexes, which is consistent with what is expected from a provider that wishes to be a reference in the passive investment space.

We cannot say as much for the practices of FTSE, where, in some cases, we conclude on a lack of transparency. We tried to find information on the multi factor indexes that made up the FTSE flagship offering in this space in 2014, namely the Diversified Factor Index series that was co-developed with JP Morgan. FTSE now publishes other multi factor indexes that follow a bottom-up approach. However, we were not able to find the old flagship offering in the official list of factor or multi factor index products on the FTSE website[38]. FTSE maintains a "JP Morgan Asset Management Factor" index series. These indexes are notably invested in UCITS funds and it is imperative for this information to be presented. However, in a concern to communicate on its flagship indexes, which allows it to reflect its investment beliefs of the moment, which are no longer those of yesterday, FTSE has chosen to position this index as a custom index that carries the brand of a partner firm, rather than as its own flagship offering. Even though it can be found on the website, if one is imaginative, it is not accessible through the Global Factor Index menu, which is supposed to represent FTSE's offering. Does this mean that FTSE has problems with its past performance or with its past investment beliefs?

Going beyond the examples mentioned, the question of the governance of index changes should be a

[36] See FTSE (2014), "Factor exposure indexes - Value factor", available at https://www.ftserussell.com/sites/default/files/research/factor_exposure_indexes-value_factor_final.pdf
[37] See "Introducing MSCI FaCS".
[38] We visited the website www.ftse.com and followed the link "Index Series, then "Factor > See All". The "JP Morgan Asset Management Factor" index series was not shown in this list.

subject of concern not only for index providers but also, and especially, for investors. Regardless of the reasons for discontinuation of indexes, disappearing indexes are unfavorable from a transparency perspective. In fact, when index methodologies disappear or are hidden, investors are no longer able to assess the quality of the index offerings through time. It is straightforward to preserve transparency by maintaining old and new index series in parallel in as visible a manner as possible. When index changes are announced, investors should get clear information on the details of these changes without requiring investors to do the detective work of comparing different versions of ground rules documents. Providers should also be transparent about the motivations behind index changes.

While frequent and unjustified changes in index methodologies and offerings heighten data-mining risks, a lack of transparency about these changes effectively prevents investors from analyzing such risks. While all indexes require transparent construction rules at any given point in time, transparency also has to apply to changes in these rules over time.

More globally, we might think that with success of smart beta index offerings, the promise of which is fairly similar to that of an active asset manager, namely beating the cap-weighted benchmark, and the elements of competition of which are the comparison with the performance of competitors, best index governance practice should also be in line with the presentation of asset manager performance promoted as part of the GIPS standards[39]. These standards would lead to the construction of composites that are representative of all the indexes produced by index providers, including those that have been discontinued, and as such would increase the transparency of the performance displayed and would eliminate the phenomena of survivorship bias and omission of historical data.

5. Conclusion

Providers of smart beta strategies frequently change index rules. These changes often create inconsistencies between different products released at different times. Such changes may affect factor definitions, factor selection, and portfolio construction principles. By giving concrete examples, we show that methodological changes are quite common in the industry and sometimes happen across multiple dimensions at the same time.

The main problem with inconsistencies across time is a data-mining risk. We have provided stylized examples to illustrate possible implications of data-snooping biases. Our analysis suggests that picking the best-performing variable as a factor definition or selecting the best-performing combination of factors on an in-sample basis may lead to a significant degradation in the out-of-sample performance. Moreover, we observed that simultaneously changing index rules in multiple dimensions, such as factor definitions, factor selection and investment principles, leads to striking differences in the performance of multi-factor indexes.

While providers will naturally change index methodologies as markets evolve and research progresses, there are important requirements to safeguard investors from facing unlimited data-mining risks.

First, a lack of transparency about index changes makes it more difficult for investors to evaluate index offerings, and exacerbates the risk of relying on spurious performance records. Therefore, providers of factor products should be transparent about the methodological changes they make.

Second, providers can put stringent requirements on index changes by remaining consistent with their investment principles. Indeed, if the urge to "innovate" means deviating from investment principles, index investors will risk being disappointed with results. Maintaining investment discipline by adhering to a set of long-term principles may be the best safeguard against negative surprises with factor indexes. Investors may be well advised to rely on providers who do not follow the latest factor fad by continuously changing their index methodologies. As Warren Buffett once said, "the stock market has a very efficient way of transferring wealth from the impatient to the patient". •

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[39] *Please refer to the following document published on January 29, 2010: https://www.cfainstitute.org/-/media/documents/code/gips/gips-standards-2010.ashx*

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A major crisis is threatening the sustainability of pension systems across the globe

The first pillar of pension systems, which is made up of public social security benefits and aims at providing a universal core of pension coverage to address basic consumption needs in retirement, is strongly impacted by rising demographic imbalances. Life expectancy at age 65 in OECD countries is expected to grow by 4.2 years for women and 4.6 years for men between 2020 and 2065. As a result, the number of individuals aged 65 and over per 100 individuals aged between 20 and 64, which rose from 13.9 in 1950 to 27.9 in 2015, is expected to grow to 58.6 by 2075.[40]

In parallel, the second pillar of pension systems, which is expected to provide additional replacement income for retirees via public or private occupational pensions, is weakening. In particular, private pension funds have been strongly impacted by the shift in accounting standards towards the valuation of pension liabilities at market rates instead of fixed discount rates, which have resulted in increased volatility for the value of liabilities. The impact of this new constraint has been reinforced by stricter solvency requirements following the 2000-2003 pension fund crisis. As a result of these changes in accounting and prudential regulations, a large number of corporations have closed their defined-benefit pension schemes to new members and increasingly to further accrual of benefits, so as to reduce the impact of pension liability risk on their balance sheets and income statements. Overall, a massive shift from defined-benefit pension schemes to defined-contribution pension schemes is taking place across the world, implying a transfer of retirement risks from corporations to individuals.

As an almost universal rule, public and private pension schemes deliver replacement income lower than labor income, and the gap is sometimes severe. According to OECD, an individual with average earnings in the United States can expect to receive merely 49.1% of labor income from mandatory pension arrangements when retiring, and the replacement rate falls to 29.0% in the United Kingdom. With the need to supplement public and private retirement benefits via voluntary contributions, the so-called third pillar of pension systems, individuals are becoming more and more responsible for their own retirement savings and investment decisions. This global trend poses substantial challenges to individuals, who often lack the expertise required to make such complex financial decisions.

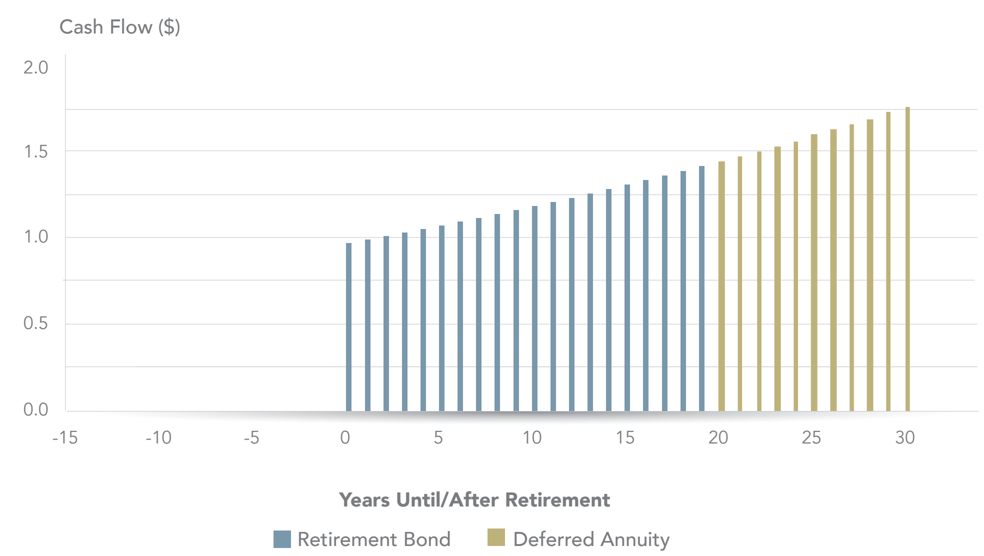
Currently available products fall short of providing a satisfactory answer to the needs of individuals preparing for retirement

In response to these concerns, a number of so-called retirement products have been proposed by insurance companies and asset management firms. Asset management products offer a wide range of investment options, but none of these options really addresses retirement needs because they neither allow investors to secure a given level of replacement income, nor explicitly intend to do so. This is also true for target date funds, even though they are often used as default options by individuals saving for retirement.

EXHIBIT 1

Cash flows of retirement bond and deferred annuity

Replacement income cash flows grow by 2% per year in order to offer a protection against rising cost of living. For the purpose of illustration, the retirement period is assumed to be 30 years, but it is actually uncertain, owing to longevity risk.



In contrast, insurance products, such as annuities and variable annuities, can secure a fixed level of replacement income throughout retirement. However, this security comes at the cost of a severe lack of flexibility, because annuitization is an almost irreversible decision, unless one is willing to bear the costs of high surrender charges, which can amount to several percentage points of the invested capital. This rigidity is a major shortcoming in the presence of life uncertainties such as marriage and children, changing jobs, health issues, changing locations to lower or higher cost cities or countries, decisions about retirement dates, etc. It also explains why annuities, while offering the security that investment products lack, are in low demand overall.[41]

To sum up, individuals are currently left with an unsatisfactory dilemma between on the one hand insurance products that provide security but lack flexibility, and on the other hand investment products that provide flexibility but no security with respect to the level of future replacement income.

Retirement bond: The safe asset in retirement investment solutions

Fortunately, existing financial engineering techniques can be used to design new forms of "flexicure" investment solutions that can offer individuals both security and flexibility when approaching retirement investment decisions, thus providing a way out of the impasse of a choice between annuities and target date funds. In a recent paper (Martellini, Milhau and Mulvey (2019)), we analyze investment decisions for individuals saving for retirement in the goal-based investing framework, which is the counterpart of the liability-driven investing framework used in institutional money management (see also Deguest et al. (2014)), and we argue that costly and quasi-irreversible annuity products are not needed to secure replacement income for a fixed period of time in retirement. To generate income for, say the first 20 years of retirement, a period that roughly corresponds to the life expectancy of a 65-year-old US individual, one can design a dedicated cash-flow-matching portfolio made up of liquid fixed-income securities. This "goal-hedging portfolio" is to future retirees what the liability-hedging portfolio is to defined-benefit pension funds, and we call it a "retirement bond" because its cash-flow schedule matches exactly the needs of retirees. Protection against the risk of living longer than expected can be achieved by purchasing a deferred late life annuity.

Exhibit 1 shows how an annuity with a cost-of-living-adjustment can be decomposed as the sum of a retirement bond, or retirement-bond-replicating portfolio, which covers the first 20 years in retirement, and a deferred late life annuity that takes care of the late retirement period. The blue bars represent the twenty cash flows of the retirement bond and the yellow ones are the cash flows (in uncertain number) of the deferred annuity that starts right after the retirement bond has matured.

Retirement bonds do not exist as off-the-shelf fixed-income products, but a series of recent articles in the financial and general press have made a case for their issuance by governments and other public or semi-public institutions. Merton and Muralidhar (2017) coin the term "SeLFIES" for "Standard of Living indexed, Forward-starting, Income-only Securities" (see also Muralidhar (2015), Muralidhar, Ohashi, and Shin (2016), Martellini, Merton,

[40] *Figures cited here are from the OECD report Pensions at a Glance 2017.*
[41] *Other explanations of the "annuity puzzle" are related to the fact that annuities involve counterparty risk and high levels of fees, and also that they do not contribute to bequest objectives.*

and Muralidhar (2018) and Kobor and Muralidhar (2018)). These bonds would enjoy the following two main characteristics: (1) payments are deferred to the retirement date, and (2) interest payment and capital amortization are spread over time in such a way that the annual income paid by the bond is constant or preferably cost-of-living-adjusted. Their price can easily be obtained by summing future cash flows discounted at market zero-coupon rates, and they can be replicated by standard factor-matching techniques like duration hedging and duration-convexity hedging, or by cash-flow matching methods that rely on the stripping of coupon-paying bonds and/or interest rate derivatives. These methods are routinely deployed in asset-liability management for the construction of liability-hedging portfolios.

These dedicated duration-matched bond portfolios are very different from the typical off-the-shelf short duration bond portfolio used by default as the "safe" component in target-date-fund strategies. The latter portfolio is actually unsafe with respect to retirees' needs because its duration does not match the duration of the targeted cash-flow schedule. As a result, it does not properly replicate the performance of the retirement bond, and there is no guarantee that it will deliver the desired cash flows in retirement.

Because the cash flows of the retirement bond are normalized to $1 per year, the purchasing power of savings in terms of replacement income is given by the nominal value of savings divided by the retirement bond price. Given an inception date for accumulation, the funding ratio is defined as the ratio of the current purchasing power to its initial value, so it is equal to the relative performance of wealth with respect to the retirement bond. Exhibit 2 shows the funding ratio for a standard bond portfolio (here taken to be the Barclays US Treasury Index with coupons reinvested), for a broad equity portfolio (the market portfolio from Ken French's website), and for the dedicated retirement bond. The accumulation period ranges from January 1998 to January 2018, and, for simplicity, no cost-of-living adjustment is included here.

By construction, the retirement bond portfolio leads to a funding ratio that stays constant over time, while in this particular sample period the equity and Treasury bond indexes failed to keep up relative to the price of the retirement bond. As a result, an investor choosing equities or a standard bond portfolio would have ended 2018 with a lower purchasing power than in 1998. Of course, performance is sample-dependent, and the sample period was marked by an almost continuous decrease in interest rates and three severe bear markets in 2000, 2002 and 2008, through which the funding ratio with equities fell respectively by 35.8%, 36.3% and 53.5%. The retirement bond portfolio benefited more from the decrease in interest rates than the standard bond index due the longer duration of the former portfolio.

Regardless of the peculiarities of the sample period, a robust insight to be gained from Exhibit 2 is that investing in the standard equity and bond portfolios generates substantial funding ratio volatility. For instance, the standard bond portfolio and the equity index imply volatility levels of respectively 11.46% and 31.30% over the sample period. This confirms that investing in a portfolio that does not take into account investors' characteristics leaves them with a substantial amount of uncertainty with respect to their replacement income.

Improved forms of target date funds as meaningful retirement solutions

The retirement bond portfolio is intended as a liquid portfolio that delivers stable and predictable replacement income. Each dollar invested in this portfolio allows the individual to secure a fixed number of dollars every year in retirement. On the other hand, and precisely because of this security, investing in the retirement bond portfolio cannot generate upside in terms of replacement income. To increase the achievable level of replacement income without relying only on additional contributions, an investor has

EXHIBIT 2

Change in the purchasing power of wealth in terms of replacement income with respect to 1998 value; 1998 – 2018.

The purchasing power of wealth in terms of replacement income equals the nominal value of savings divided by the price of the retirement bond that delivers a replacement income of $1 per year. The change shown in this figure is the ratio of the current value to January 1998 value.

EXHIBIT 3

Change in purchasing power of wealth in terms of replacement income with respect to 1998 level; 1998 – 2018.

Both target date funds start with a 60% allocation to equities in 1998 and let it gradually decrease down to 20% in 2018. The second building block is a standard bond portfolio (the Barclays US Treasury index) in the standard fund, and the retirement bond in the improved fund.

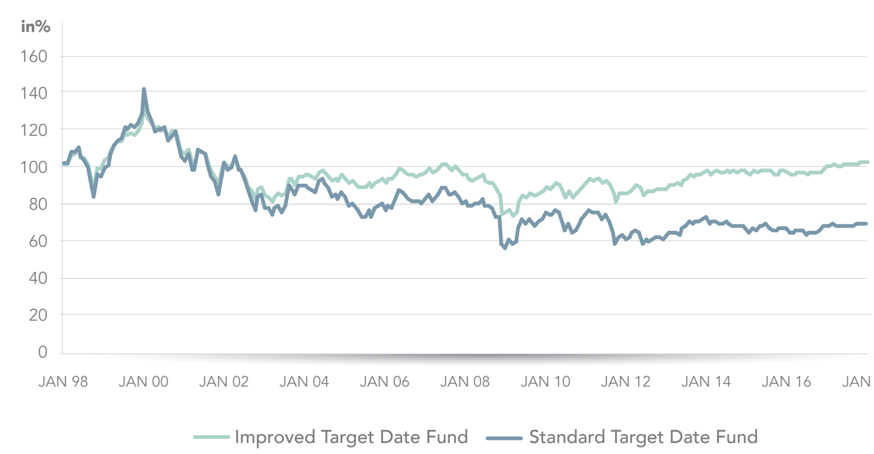
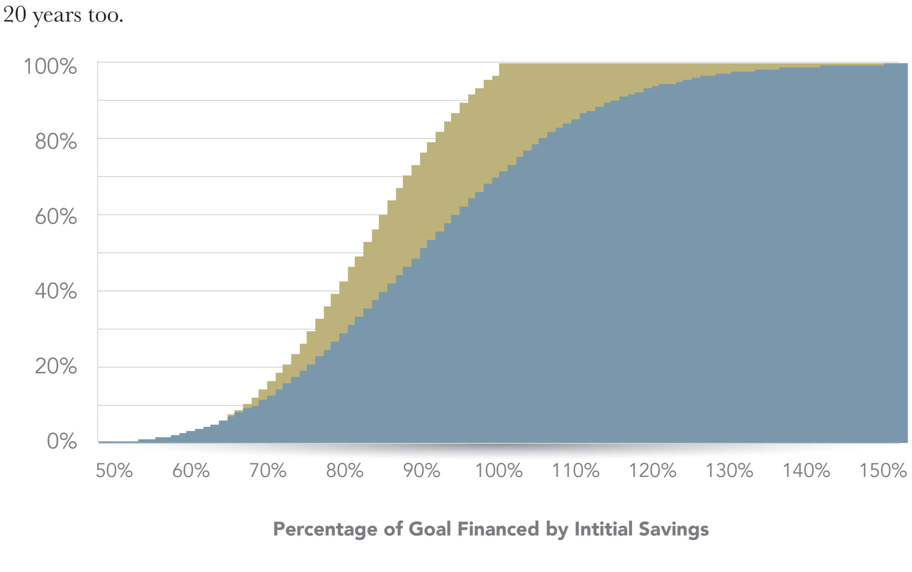


EXHIBIT 4

Probability of reaching aspirational goal by retirement date.

Probabilities are estimated by Monte-Carlo simulations. The horizontal axis represents the percentage of the target retirement income level that is fulfilled with initial savings. A scenario is categorized as successful if the investor reaches 100% of the target at least once before retirement (for the improved target date fund), or at the retirement date (for the standard fund). Initial time to retirement is 20 years, and the decumulation period is 20 years too.



To evaluate the adequacy of an investment solution for an individual, absolute performance is of little relevance.

to take some risk and invest in assets that are expected to outperform the retirement bond in the long run. A well-diversified equity fund would be a good example of such a "performance-seeking portfolio".

Let us consider as a starting point a target date fund that lets the equity allocation gradually decrease from 60% in 1998 down to 20% in 2018, and construct an "improved" version by replacing the bond portfolio with the retirement bond that starts paying off at the investor's retirement date. The equity component and the glide path remain unchanged. Unlike the standard target date fund, the improved target date fund explicitly takes into account the nature of the goal (which is to produce replacement income) as well as the investor's retirement date and decumulation period.

In what follows, we show that the use of the retirement bond in place of the standard bond portfolio leads to substantial improvements in terms of replacement income. To give a first sense of these benefits, Exhibit 3 shows the simulated funding ratios obtained with the standard and improved target date funds.

In this particular sample period, the improved target date fund outperformed its standard counterpart because the retirement bond itself outperformed the bond index. Indeed, the retirement bond benefitted more from the decrease in interest rates because of its longer duration. Across a large number of scenarios, the retirement bond portfolio is actually expected to outperform on average the bond index provided there is a positive premium associated with interest rate risk.

Another consequence of the substitution of the standard bond portfolio with the proper goal-hedging portfolio is that the purchasing power of wealth in terms of replacement income displays less variability over time. Numerically, the volatility of annual changes in the funding ratio decreases from 19.09% to 13.54%. The explanation is straightforward because a perfect goal-hedging portfolio has by definition zero tracking error with respect to the retirement bond. Similar results are obtained by replacing the standard bond portfolio with the retirement bond in a balanced fund, which maintains a fixed-mix allocation to the equity and the bond building blocks (see Martellini, Milhau and Mulvey (2019)).

Probabilities of reaching "aspirational" levels of replacement income

To evaluate the adequacy of an investment solution for an individual, absolute performance is of little relevance. Performance is only useful to the extent that it serves goal achievement, so a better metrics is the ex-ante probability of reaching an aspirational goal, defined as a target level of replacement income that the individual was unable to finance at the beginning of accumulation.

Exhibit 4 shows the probabilities of reaching the target income level with both the standard and the improved target date funds introduced above. These probabilities are estimated with a Monte-Carlo model for the returns of the performance-seeking portfolio – modeled as a broad equity index –, as well as the return of the standard bond portfolio and of the retirement bond.[42] The horizontal axis represents the percentage of the target income level that can be financed with initial savings. When it is less than 100%, the target income level is a genuine "aspirational" goal because it cannot be financed with initial savings.

For all values of the initial funding ratio, the improved fund generates higher success probabilities measured in terms of probabilities to reach full funding. The benefit of using the improved target date fund is relatively small for severely under-funded individuals, but becomes substantial for initial funding levels starting at 80% and above.

It should be emphasized at this stage that even the improved target fund can experience substantial short-term losses in terms of funding ratio. To address this concern, Martellini, Milhau and Mulvey (2019) introduce a class of risk-controlled portfolio strategies, which adapt standard portfolio insurance techniques to the management of relative risk with respect to the retirement bond, and show that they are effective at capping the size of losses within a given time frame (e.g., one year) to a pre-specified threshold.[43]

Individuals should not have to choose between security and flexibility when approaching retirement investment decisions

In this article, we propose to apply the principles of goal-based investing to the design of a new generation of "flexicure" retirement investment strategies, which aim at offering the best-of-both-worlds between insurance products and asset management products. These strategies can be used to help individuals and households secure minimum levels of replacement income while generating upside exposure through liquid and reversible investment products. In implementation, recent advances in financial engineering and digital technologies make it possible to apply goal-based investing principles to a much broader population of investors than the few traditional clients who can afford customized mandates or private banking services. This environment creates an opportunity to provide genuine investment solutions, as opposed to off-the-shelf products, to individuals preparing for retirement.

The pension crisis will not be solved by financial engineering alone. Part of the solution lies in the hands of individuals themselves, who need to start contributing more and earlier so as to more efficiently complement the benefits expected from the first two pillars of pension systems. However, the investment industry does face an ever greater responsibility to provide suitable retirement solutions, especially to individuals who are unfamiliar with basic financial concepts and are therefore not in a position to make educated investment decisions.

In a recent joint initiative, EDHEC-Risk Institute and the department of Operations Research and Financial Engineering (ORFE) at Princeton University have teamed up to design a series of indexes called the "EDHEC-Princeton Retirement Goal-Based Investing Index series", which are published on EDHEC-Risk Institute and Princeton ORFE websites (see https://risk.edhec.edu/indices-investment-solutions for more details). It is our hope and ambition that this initiative, as well as related work, can facilitate the introduction of second-generation flexicure target date funds that will be used as part of the solution to the global pension crisis. After all, similar techniques are routinely used in liability-driven investment solutions designed for the benefit of institutional investors, and transporting them to individual money management would be a worthwhile and long-awaited endeavor. •

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[42] For the individual who invests in the improved target date fund, probabilities are calculated by implementing a stop-gain mechanism that consists of shifting the entire wealth to the retirement bond whenever the target level of replacement income is achievable. This approach is not available for individuals investing in the standard target date funds because the safe retirement bond is by assumption not available to them.

[43] Downside protection is arguably most critical for individuals approaching retirement, as there is then very little time left to recover from a loss that can wipe out a fraction of accumulated retirement savings, and the risk budget can be set to decrease over time. For this very reason, one may be tempted to introduce a risk budget, or a multiplier, that decreases over time.

Implementable Unconditional and Conditional Carry Strategies in the US Treasury Market

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Most excess return studies in Treasuries have concentrated to date on the profitability of unconditional "carry" strategies, i.e., strategies where the investment on a N-maturity (zero-coupon) bond is held for a holding period (typically of one year) and is funded by the sale of a short bond expiring at the end of the investment period[44]. These strategies are designed to capture in the long run the level/duration risk premium (indeed, if the expectation hypothesis were true, no excess returns should be reaped) and they have been profitable over long samples, as Figure 1 shows for data spanning the 1971-2017 period. The most commonly adduced explanation for this profitability is the existence of a positive risk premium associated with bearing "duration" risk (Fama and Bliss (1987), Campbell and Shiller (1991)). A finer analysis shows that the carry strategies have been profitable during recessions, unprofitable during expansions, and particularly unprofitable in the second half of the recorded expansions, suggesting that the market price of risk must be time-varying and depend on state variables linked to the business cycle, starting with the slope of the yield curve.

More recent work in the mid-2000s (Cochrane and Piazzesi (2005), Ludvigson and Ng (2009), Cieslak and Povala (2015)) has suggested that the return-predicting factor(s), i.e., quantities that are supposed to explain the observed excess returns, may be more complex than originally envisaged, but after the 1990s the existence of a positive duration risk premium has rarely been put in doubt.

It must be stressed, however, that virtually all the studies that have appeared in the academic literature have made use of 'virtual' discount bonds obtained by best fit to actual Treasury prices. Unfortunately, this translation from actual prices of coupon-bearing bonds to virtual prices of discount bonds is not unproblematic, since some of the distinguishing features of the new-generation return-predicting factors (such as the 'tent' shape) can disappear when slightly different construction methods are used to build the discount bond. It is therefore not obvious whether the high degree of predictability found using discount bonds by Cochrane and Piazzesi (2005), Ludvigson and Ng (2009), Cieslak and Povala (2015) and others survives when actual CUSSIP-level data are used. To the best of our knowledge, no studies of the profitability of the new and old risk factors using CUSIP-level data have appeared in the literature. This article attempts to fill this gap.

FIGURE 1

Zero-Coupon Carry Strategies Main Statistics

This figure reports the average returns, standard deviations and Sharpe ratios from the carry strategies (1-year investment period for US Treasuries from 1971 to 2017. Zero-coupon bond prices are from Gürkaynak et al. (2007).

MATURITY	2	3	4	5	6	7	8	9	10
AVERAGE	0.53%	0.96%	1.32%	1.63%	1.90%	2.13%	2.32%	2.48%	2.62%
STANDARD DEVIATION	1.73%	3.15%	4.38%	5.51%	6.58%	7.61%	8.61%	9.60%	10.58%
SHARPE RATIO	0.30	0.30	0.30	0.30	0.29	0.28	0.27	0.26	0.25

Unconditional long/short carry strategies with CUSIP bonds

In what follows we propose a detailed empirical study of implementable unconditional and conditional carry strategies in the US Treasury market so as to assess whether the level factor remains conditionally and unconditionally rewarded when strategies are implemented using actually traded bonds rather than "virtual" discount bonds.[45]

Our universe is made up of 1,720 coupon bonds over the period December 27, 1973 to June 29, 2018.[46] We split, at each end-of-month date, all the available bonds into four maturity buckets:

- bonds with maturities ranging from 1 to 3 years (bucket 1);
- 3 to 5 years (bucket 2);
- 5 to 10 years (bucket 3);
- and higher than 10 years (bucket 4).

Since the time-to-maturity of every bond decreases over time and new bonds are regularly issued, the number of bonds in each bucket and the composition of each bucket vary over time. We define, for each bucket, an equally-weighted portfolio of all bonds in the bucket and perform monthly rebalancing back to this equally-weighted target.[47] We further assume that each coupon paid by a given bond is reinvested in the same bond.

Figure 2 reports the main descriptive statistics for the four aforementioned portfolios. The median duration of the maturity bucket portfolios (taken over all dates) are 1.7, 3.4, 5.5 and 10.9 years. We note that time average and median values are close for maturity, duration and number of bonds, suggesting that the underlying distributions are relatively symmetric. The minimum and median number of bonds in the four portfolios are respectively 13, 4, 9, 13 for the minimum value and 47, 32, 33.5, 32 for the median value, ensuring a sufficiently large number of bonds in each bucket.

The annualized mean return and annualized volatility of the four portfolios respectively are 5.9%, 6.6%, 7.0%, 8.4% and 2.8%, 4.6%, 6.4%, 9.7% which indicates that bonds with higher maturity are riskier but better compensated. Sharpe ratios, which respectively are 0.44, 0.43, 0.37 and 0.39, suggest that the reward per unit of risk is higher for shorter maturity.

We first examine at CUSIP level the profitability of unconditional and conditional long-short carry strategies. For the period under analysis (December 27, 1973 to June 29, 2018) we engage in an unconditional carry strategy using the 4 bucket portfolios as building blocks, so as to avoid inconsistencies related to the use of single bonds. More precisely, we compute at the end of each month a 1-year investment horizon buy-and-hold zero-cost long/short carry strategy where the long leg is a given maturity bucket and the short leg is an equally-weighted portfolio of the 3 bonds in the 1-3Y maturity bucket with the lowest maturities. We made this choice for the short leg in order to have a duration as close as possible to the investment horizon (and hence to have the lowest possible duration risk for the funding leg). We consider the 3-5Y, 5-10Y and 10Y+ maturity bucket portfolios, and therefore three possible cases, for the long leg construction. For each of the three carry strategies considered, we obtain over the period 523 annual excess returns with monthly overlap.

The results are shown in Figure 3, which displays the mean excess return, the volatility, the Sharpe ratio, the minimum excess return and the maximum excess return for the three zero-cost long/short carry strategies. The results we obtain are consistent with those obtained with fictitious zero-coupon bonds in that all the strategies display a performance level that is positive and statistically different from zero, with mean excess returns ranging from 1.2% to 3.1%. We observe that both the mean excess return and the volatility increase with the maturity of

44 The returns are given by: $xret^N_{t\rightarrow t+1} = p^{N-1}_{t+1} - p^N_t - y^1_t = (y^N_t - y^{N-1}_{t+1})(N-1) + (y^N_t - y^1_t)$ where p^N_t denotes the time-t log price of a N-maturity bond and y^N_t its yield.

45 We thank ICE for providing us with the dataset used for our empirical analysis.

46 All these bonds are non-callable and non-puttable.

47 This rebalancing frequency choice is meant to maintain the portfolio well diversified and keep its duration as stable as possible as time goes by.

bucket portfolio chosen for the long leg of the strategy, a result which is again consistent with the findings obtained with zero-coupon bonds. On the other hand, we do not find the monotonic relationship between the Sharpe ratio and the duration of the long leg strategy that was obtained in the US zero-coupon bond universe.

Overall, these results suggest that an unconditional carry strategy is positively rewarded at the CUSIP level, which is consistent with the existence of a positive bond risk premium associated with an exposure to changes in the level of interest rates.

Bond returns predictability and level risk factor

Next, we study from a conditional perspective the level risk factor and define three signals that have been recognzed in the academic literature for their ability to predict the variation of bond returns. The factor construction is implemented in practice as described below.

The Slope return predicting factor at time t is simply defined as the difference between the 15-year zero-coupon yield and the 2-year zero-coupon rate.[48]

For the Cochrane-Piazzesi return predicting factor, the procedure is the following:

1. For n = 2...15, we first compute the n-year zero-coupon bond excess returns as:

$$xret^{N}_{t\rightarrow t+1} = p^{N-1}_{t+1} - p^{N}_{t} - y^{1}_{t} = (y^{N}_{t} - y^{N-1}_{t+1})(N-1) + (y^{N}_{t} - y^{1}_{t})$$

2. Then we define the vector x_t as $x_t = [1; f^{3}_{t}; f^{6}_{t}; f^{9}_{t}; f^{12}_{t}; f^{15}_{t}]^{t}$ where $(f^{i}_{t})_{i=3,6,9,12,15}$ refers to the 1-year forward rates i years from date t.[49]

3. We run 14 regressions of excess returns time-series on the five forward rates time-series

$$xret^{N}_{t\rightarrow t+1} = \psi^{(n)} x_t + \varepsilon_t).$$

and obtain the 14 corresponding individual maturity-dependent return-predicting factor time series

$$\psi^{(n)} x_t,\ n = 2...\ 15.$$

4. The Cochrane-Piazzesi (CP in short) signal at time t is finally obtained by averaging the individual maturity-dependent return-predicting factors across maturities.

The procedure to compute the Cielsak-Povala return predicting factor is the following:

1. For $n = 2...15$, we first compute the n-year zero-coupon bond excess returns.

2. Then we define the vector x_t as x_t $[1; c^{3}_{t}; c^{6}_{t}; c^{9}_{t}; c^{12}_{t}; c^{15}_{t}]^{t}$ where $(c^{i}_{t})_{i=3,6,9,12,15}$ refers to the i-year yield cycles at date t.[50]

3. We run 14 regressions of excess returns time-series on the five cycles time-series

$$xret^{N}_{t\rightarrow t+1} = \psi^{(n)} x_t + \varepsilon_t).$$

and obtain the 14 corresponding individual maturity-dependent return-predicting factor time series

$$\psi^{(n)} x_t,\ n = 2...\ 15.$$

FIGURE 2

Statistics for maturity buckets

This figure contains the main descriptive statistics of the four following maturity buckets: 1 to 3 years, 3 to 5 years, 5 to 10 years and higher than 10 years. Each maturity bucket refers to an equally-weighted monthly rebalanced portfolio of all the bonds that have a time-to-maturity matching the bucket. Coupons, when paid, are assumed to be reinvested in the same bond. These numbers are computed with monthly returns over the backtesting period December 27, 1973 to June 29, 2018. The risk-free rate is the 3-month T-bill rate.

	1-3Y	3-5Y	5-10Y	10Y+
Annualized Mean Total Return	5.9%	6.6%	7.0%	8.4%
Annualized Volatility	2.8%	4.6%	6.4%	9.7%
Sharpe Ratio	0.44	0.43	0.37	0.39
Monthly Minimum Excess Return	-3.6%	-5.7%	-7.0%	-9.1%
Monthly Maximum Excess Return	8.2%	11.2%	13.4%	15.4%
	1-3Y	3-5Y	5-10Y	10Y+
Average Maturity	1.9	4.0	7.2	19.5
Median Maturity	1.9	4.0	7.2	19.2
Minimum Maturity	1.7	3.7	6.3	14.4
Maximum Maturity	2.1	4.3	8.1	24.1
	1-3Y	3-5Y	5-10Y	10Y+
Average Duration	1.8	3.4	5.7	10.8
Median Duration	1.7	3.4	5.5	10.9
Minimum Duration	1.5	2.9	4.4	6.7
Maximum Duration	2.0	3.9	6.8	16.5
	1-3Y	3-5Y	5-10Y	10Y+
Average # Bonds	50.7	32.6	35.3	34.5
Median # Bonds	47.0	32.0	33.5	32.0
Minimum # Bonds	13.0	4.0	9.0	13.0
Maximum # Bonds	104.0	69.0	71.0	61.0

FIGURE 3

Statistics for L/S $-neutral carry strategies

This figure displays the mean excess return, volatility, Sharpe ratio, minimum excess return and maximum excess return of the long/short dollar-neutral carry strategies over the backtesting period December 27, 1973 to June 29, 2018. The backtesting period contains 523 monthly overlapping 1-year investment periods. We also report the Newey-West t-test for the mean excess return on the last row.

	3-5Y	5-10Y	10Y+
Mean Excess Return	1.2%	1.6%	3.1%
Volatility	3.4%	5.4%	9.1%
Sharpe Ratio	0.34	0.29	0.34
Minimum Excess Return	-9.1%	-14.0%	-17.6%
Maximum Excess Return	10.0%	18.1%	35.2%
Newey-West t-test	4.13	3.57	4.08

[48] We take into account maturities up to 15-year in the computation of the signals since the maturity bucket portfolio with the highest duration is made of bonds with duration up to 16.5 years.
[49] The superscript T means "transpose".
[50] The cycle factor, defined in Cieslak and Povala (2015), is a proxy for the time-varying risk premium across the whole maturity bond spectrum.

FIGURE 4

Unconditional Long/Short Dollar-Neutral Carry Strategies Statistics under Different Regimes

This figure contains the main statistics of the unconditional long/short dollar-neutral carry strategies under the different slope, CP and CiP regimes.

	3-5Y	5-10Y	10Y+	3-5Y	5-10Y	10Y	+3-5Y	5-10Y	10Y+
	UNCONDITIONAL			UNCONDITIONAL			UNCONDITIONAL		
Annualized Mean Excess Return	1.2%	1.6%	3.1%	1.2%	1.6%	3.1%	1.2%	1.6%	3.1%
Annualized Volatility	3.4%	5.4%	9.1%	3.4%	5.4%	9.1%	3.4%	5.4%	9.1%
Sharpe Ratio	0.34	0.29	0.34	0.34	0.29	0.34	0.34	0.29	0.34
Monthly Minimum Excess Return	-9.1%	-14.0%	-17.6%	-9.1%	-14.0%	-17.6%	-9.1%	-14.0%	-17.6%
Monthly Maximum Excess Return	10.0%	18.1%	35.2%	10.0%	18.1%	35.2%	10.0%	18.1%	35.2%
	LOW SLOPE			LOW COCHRANE-PIAZZESI			LOW CIESLAK-POVALA		
Annualized Mean Excess Return	0.5%	0.3%	0.6%	0.2%	-0.1%	0.0%	-1.3%	-2.6%	-4.3%
Annualized Volatility	3.7%	5.6%	8.4%	3.2%	5.1%	8.4%	2.9%	4.5%	6.7%
Sharpe Ratio	0.14	0.05	0.07	0.07	-0.03	0.00	-0.46	-0.58	-0.64
Monthly Minimum Excess Return	-8.4%	-13.6%	-17.6%	-9.1%	-14.0%	-17.6%	-9.1%	-14.0%	-17.6%
Monthly Maximum Excess Return	9.1%	13.4%	22.9%	8.6%	14.3%	25.8%	5.7%	7.2%	15.8%
	MEDIUM SLOPE			MEDIUM COCHRANE-PIAZZESI			MEDIUM CIESLAK-POVALA		
Annualized Mean Excess Return	0.8%	0.8%	1.8%	0.4%	0.6%	1.9%	1.1%	1.4%	2.8%
Annualized Volatility	3.0%	4.8%	7.9%	3.1%	5.0%	8.8%	2.7%	4.1%	6.9%
Sharpe Ratio	0.25	0.17	0.23	0.13	0.11	0.21	0.40	0.35	0.41
Monthly Minimum Excess Return	-7.6%	-12.6%	-14.3%	-7.7%	-12.1%	-16.8%	-5.7%	-10.0%	-13.4%
Monthly Maximum Excess Return	10.0%	18.1%	34.0%	9.1%	15.4%	28.3%	8.6%	12.5%	27.9%
	HIGH SLOPE			HIGH COCHRANE-PIAZZESI			HIGH CIESLAK-POVALA		
Annualized Mean Excess Return	2.2%	3.7%	6.8%	2.8%	4.4%	7.3%	3.8%	6.0%	10.3%
Annualized Volatility	3.1%	5.2%	9.9%	3.2%	5.0%	8.6%	2.8%	4.5%	7.8%
Sharpe Ratio	0.70	0.72	0.68	0.89	0.86	0.85	1.37	1.35	1.31
Monthly Minimum Excess Return	-9.1%	-14.0%	-15.3%	-6.9%	-10.8%	-13.2%	-3.0%	-4.6%	-6.5%
Monthly Maximum Excess Return	9.2%	17.5%	35.2%	10.0%	18.1%	35.2%	10.0%	18.1%	35.2%

4. The Cielsak-Povala (CiP in short) signal at time t is finally obtained by averaging the individual maturity-dependent return-predicting factors across maturities.

For a given signal and a given zero-cost carry strategy, we split the 523 monthly overlapping excess returns into 3 different subsets labelled as "low", "medium" and "high" regimes. More precisely, we observe the value of the signal at date t and assign the corresponding excess return between date t and $t + 1$ (in years) to the low regime subset if the signal at date t is in the first tercile, to the medium subset if it belongs to the second tercile and to the high regime subset otherwise.

Figure 4 details the main statistics for the returns of the three zero-cost carry strategies, both unconditionally (for comparison) and under the different signal regimes. It is clear from the results in this table that all the signals are strongly informative. For instance, the long/short 10Y+ carry strategy displays unconditional mean excess return of 3.1% and a Sharpe ratio of 0.34. This should be contrasted with the average performance of this strategy in high slope, high CP and high CiP regimes, which returns as high as 6.8%, 7.3% and 9.9% and corresponding Sharpe ratios of 0.68, 0.85 and 1.33 (respectively). Conversely, the carry strategies conditioned on low slope, low CP and low CiP regimes displays strongly lower mean return and Sharpe ratios than the corresponding unconditional quantities (the Sharpe ratio, in particular, moves from approximately 0.30 for three maturity buckets when measured unconditionally, to values as low as -0.64 (for the CiP signal). Overall, these results suggest that it is possible, through the use of relevant signals such as Cielsak-Povala, to predict when investors are more or less compensated for bearing duration risk.

These CUSIP-level strategies, however, require the shorting of bonds, and, therefore, cannot be implemented by investors with long-only constraints. We therefore investigate in the next section how one can design implementable long/only portfolios that take advantage of the (conditionally) rewarded level/duration risk factor.

Long-only carry portfolios

The long/short approach described above would be difficult to implement in practice because it requires the shorting of some bonds. We therefore now present a long-only framework to check whether the benefits of conditional carry strategies are robust with respect to the presence of realistic no-short-sales constraints.

To do so, we first define a benchmark portfolio as a linear combination of the 4 equally-weighted maturity bucket portfolios of US government coupon bonds presented in the previous Section: 1-3Y (referred as BB1), 3-5Y (BB2), 5-10Y (BB3) and 10Y+ (BB4). The benchmark portfolio is initially equally-weighted and rebalanced once a year.[51] Figure 5 illustrates the rationale behind the implementation of our unconditional and conditional carry portfolios: at each rebalancing date each carry portfolio strategy, whether unconditional or conditional, is defined as the addition of the benchmark portfolio and a zero-cost long/short overlay strategy.[52] The overlay strategies are designed to take a long duration risk exposure (via overlay(+)) or a short

[51] This choice has been made in accordance to the predictive power of the signals on bond returns. A higher rebalancing frequency would a priori lead to a loss of predictive power.
[52] The initial date is a rebalancing date by construction.

duration risk exposure (via overlay(−)), as a function of the signals generated by the return predictive factors. The amplitude of the duration bet is controlled via the parameter X, for which we test 5 possible values: 5%, 10%, 15%, 20% and 25%.

We define the unconditional carry portfolio as the addition of the benchmark and the long-duration overlay at each yearly rebalancing date.[53] This portfolio has by construction a longer duration exposure than the benchmark. To fix ideas, if we set X = 25% then the unconditional carry portfolio is equivalent to a 100% investment into the BB4 maturity bucket portfolio at all dates.

For a given signal, we then build a conditional carry portfolio as follows: on each yearly rebalancing date we observe in what historical tercile the signal is, and then:

- if the signal is in the low (historical)[54] tercile the conditional carry portfolio is given by the benchmark plus the short-duration overlay,
- if the signal is in the medium tercile the conditional portfolio coincides with the benchmark; and
- if the signal is in the high tercile, the conditional carry portfolio is given by the benchmark plus the long-duration overlay.

Figure 6 summarizes the main statistics for the benchmark, the unconditional carry portfolios and the conditional carry portfolios for the signals based on the three return-predicting factors (slope, Cochrane-Piazzesi and Cielsak-Povala).

We obtain that all unconditional carry portfolios have a higher annualized mean return than the benchmark (up to 8.4% for versus 7.0%), which again is consistent with the proof-of-concept results showing that the duration risk is rewarded. As expected given their higher duration (average duration up to 10.84 versus 5.43 years), these unconditional long-only carry portfolio strategies appears to be riskier than their benchmark, with a higher volatility (up to 9.7% versus 5.6%), and a higher max drawdown level (up to 18.5% versus 10.3%). These carry portfolio strategies also generate high tracking errors (ranging from 2.8% to 4.6% for X ranging from 15% to 25%) and slightly lower Sharpe ratios (ranging from 0.39 to 0.41) than the benchmark value (0.41). While these unconditional carry portfolios therefore appear to be attractive from an absolute performance point of view, the overall risk, the difference of duration with respect to the benchmark and the resulting tracking error of the unconditional carry portfolios remain substantial.

Moving to the conditional carry strategies based on the three signals detailed above and comparing them to the unconditional carry strategies, we find that they display an overall lower risk (lower volatility and lower maximum drawdown), a lower average duration absolute difference with respect to the benchmark and also a lower tracking error. The slope-based and CP-based conditional carry strategies have better Sharpe ratios (up to 0.47 for the slope-based ones and up to 0.55 for the CP-based ones) even if their average performances are a bit lower than the unconditional carry strategies. On the other hand, the Cielsak-Povala conditional carry strategies outperforms the unconditional carry strategies on all levels: for X = 25%, we this obtain higher average annualized performance (9.0% versus 8.4%), lower volatility (5.8% versus 9.7%), higher Sharpe ratio (0.75 versus 0.39), lower tracking error (3.0% versus 4.6%), higher information ratio (0.68 versus 0.31), average duration close to the benchmark average duration (5.02 versus 10.84), lower average absolute duration difference with respect to the benchmark (2.87 versus 5.41), substantially lower maximum drawdown levels (8.6% versus 18.5%) and better hit ratio (74% versus 55%). This may be due to the fact that the set of conditional CiP-based carry strategies take advantage of both the long-term positive reward of the duration risk factor and the bond return predictability. •

FIGURE 5

Decomposition of the Unconditional and Conditional Carry Portfolios
This figure explains the rationale behind the construction of the unconditional and conditional carry portfolios as the addition, at each rebalancing date, of the benchmark and an overlay.

	Bucket 1	Bucket 2	Bucket 3	Bucket 4
Benchmark	25%	25%	25%	25%
Overlay (+)	-X%	-X%	-X%	+3X%
Overlay (-)	+3X%	-X%	-X%	-X%
	Bucket 1	**Bucket 2**	**Bucket 3**	**Bucket 4**
UNCONDITIONAL STRATEGY (X=25%)	0%	0%	0%	100%
	Bucket 1	**Bucket 2**	**Bucket 3**	**Bucket 4**
CONDITIONAL STRATEGY (X=25%)				
If signal in the lower tercile	100%	0%	0%	0%
If signal in the medium tercile	25%	25%	25%	25%
If signal in the higher tercile	0%	0%	0%	100%

CONCLUSION

Carry strategies with CUSIP bonds are profitable, even when a long-only constraint is added. The use of return-predicting factors such as Cielsak-Povala allows to significantly enhance the risk-adjusted performance of the conditional carry strategy.

Maeso, Martellini and Rebonato (2018) analyze in more details the conditional CiP-based carry strategies and also demonstrate that (1) a CUSIP-level, long-only CiP-based conditional strategy effectively limits the negative impact (with respect to the benchmark) of an increasing interest rate scenario and that (2) the same CUSIP-level, long-only CiP-based conditional strategy outperforms the benchmark in all equity market scenarios, and particularly so in the case of a bear equity scenario, which makes them even more appealing in a multi-asset context.

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[53] The portfolio is buy-and-hold between two rebalancing dates. The reader will note that, unlike the long/short results where we dealt with 1-year monthly overlapping rebalancing investment period, the long/only framework differs since the yearly-rebalanced portfolios are invested over the entire period.
[54] We acknowledge the existence of a look-ahead bias in the procedure. A possible way to solve this bias would have been to split the history in two, estimate the limits of the terciles on the first part of the history and then apply the procedure to the second part. However, it would have substantially decreased the depth of our history sample.

FIGURE 6

Conditional Long-Only Carry Portfolios

This figure reports, for different values of X% the conditional long-only carry portfolios main statistics: annualized mean total return, annualized volatility, Sharpe ratio, tracking error, information ratio, average duration, absolute duration difference with respect to the benchmark, maximum drawdown, 1-way annualized turnover and hit ratio. The hit ratio is computed as the ratio of the number of months where the carry strategy has outperformed the benchmark over the total number of monthly return observations. The benchmark and unconditional carry portfolios statistics are also reported.

	BENCHMARK	CARRY PORTFOLIOS				
		UNCONDITIONAL				
		X=5%	X=10%	X=15%	X=20%	X=25%
Annualized Mean Total Return	7.0%	7.3%	7.6%	7.8%	8.1%	8.4%
Annualized Volatility	5.6%	6.4%	7.2%	8.0%	8.9%	9.7%
Sharpe Ratio	0.41	0.41	0.40	0.40	0.39	0.39
Tracking Error	0.0%	0.9%	1.9%	2.8%	3.7%	4.6%
Information Ratio	0.00	0.31	0.31	0.31	0.31	0.31
Average Duration	5.43	6.51	7.59	8.68	9.76	10.84
Average Duration Abs. Diff.	0.0	1.08	2.17	3.25	4.33	5.41
Maxdrawdown	10.3%	12.0%	13.6%	15.3%	16.9%	18.5%
Hit Ratio				55%		
		CONDITIONAL STRATEGY 1 (SLOPE)				
		X=5%	X=10%	X=15%	X=20%	X=25%
Annualized Mean Total Return	7.0%	7.1%	7.2%	7.4%	7.5%	7.6%
Annualized Volatility	5.6%	5.6%	5.7%	5.8%	6.1%	6.3%
Sharpe Ratio	0.41	0.44	0.46	0.47	0.47	0.47
Tracking Error	0.0%	0.7%	1.4%	2.1%	2.7%	3.4%
Information Ratio	0.00	0.19	0.19	0.19	0.19	0.18
Average Duration	5.43	5.53	5.64	5.74	5.84	5.95
Average Duration Abs. Diff.	0.00	0.62	1.23	1.84	2.45	3.06
Maxdrawdown	10.3%	8.7%	9.2%	11.0%	12.8%	14.5%
Hit Ratio				70%		
		CONDITIONAL STRATEGY 2 (COCHRANE-PIAZESSI)				
		X=5%	X=10%	X=15%	X=20%	X=25%
Annualized Mean Total Return	7.0%	7.3%	7.5%	7.8%	8.1%	8.3%
Annualized Volatility	5.6%	5.7%	5.8%	6.1%	6.4%	6.7%
Sharpe Ratio	0.41	0.46	0.49	0.52	0.53	0.55
Tracking Error	0.0%	0.7%	1.4%	2.0%	2.7%	3.4%
Information Ratio	0.00	0.39	0.39	0.39	0.39	0.39
Average Duration	5.43	5.48	5.52	5.57	5.61	5.66
Average Duration Abs. Diff.	0.00	0.64	1.27	1.90	2.53	3.16
Maxdrawdown	10.3%	8.7%	7.3%	8.4%	9.6%	11.1%
Hit Ratio				70%		
		CONDITIONAL STRATEGY 3 (CIELSAK-POVALA)				
		X=5%	X=10%	X=15%	X=20%	X=25%
Annualized Mean Total Return	7.0%	7.4%	7.8%	8.2%	8.6%	9.0%
Annualized Volatility	5.6%	5.5%	5.5%	5.5%	5.6%	5.8%
Sharpe Ratio	0.41	0.50	0.57	0.64	0.70	0.75
Tracking Error	0.0%	0.6%	1.2%	1.8%	2.4%	3.0%
Information Ratio	0.00	0.67	0.67	0.67	0.67	0.68
Average Duration	5.43	5.35	5.27	5.18	5.10	5.02
Average Duration Abs. Diff.	0.0%	0.58	1.16	1.73	2.30	2.87
Maxdrawdown	10.3%	8.7%	7.2%	6.8%	7.7%	8.6%
Hit Ratio				74%		

Explaining Unlisted Infrastructure Asset Prices

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Unlisted infrastructure prices have increased considerably over the past decade. Was it a bubble or a normal phenomenon?

In new research from the EDHEC Infrastructure Institute (EDHECinfra) we show that systematic risk factors can largely explain the evolution of average prices but also that valuations have shifted to a higher level. We show that unlisted infrastructure equity prices do not exist in a vacuum but are driven by factors that can be found across asset classes.

Six factors are found to explain the market prices of unlisted infrastructure investments over the past 15 years: size, leverage, profits, term spread, value and growth. To these usual suspects, one can add sector and geographic effects. The result is an unbiased view of the evolution of prices (price-to-sales and price-to-earnings ratios).

We also find that on top of standard risk factors associated with most firms, sector specific factors explain the level of prices and their recent evolution. For instance, renewable energy projects are found to have much higher price-to-sales ratios than average infrastructure companies, while social infrastructure has lower than average price-to-sales and roads valuations trend up and down with the economic cycle.

Our analysis documents the contribution of these factors to the evolution of average prices over the past fifteen years. Their effect is found to have been mostly persistent over this period i.e. individual risk premia have been stable albeit, in some cases, time-varying. These effects are thus likely to continue driving prices in the future.

At the aggregate level, we document a degree of covariance between unlisted infrastructure prices and equivalent measures in public equity markets. At the sector level, patterns emerge with higher correlation with public markets in certain sectors more exposed to the economic cycle (e.g. Roads) and others experiencing peaks followed by a decrease in prices, like in the power sector.

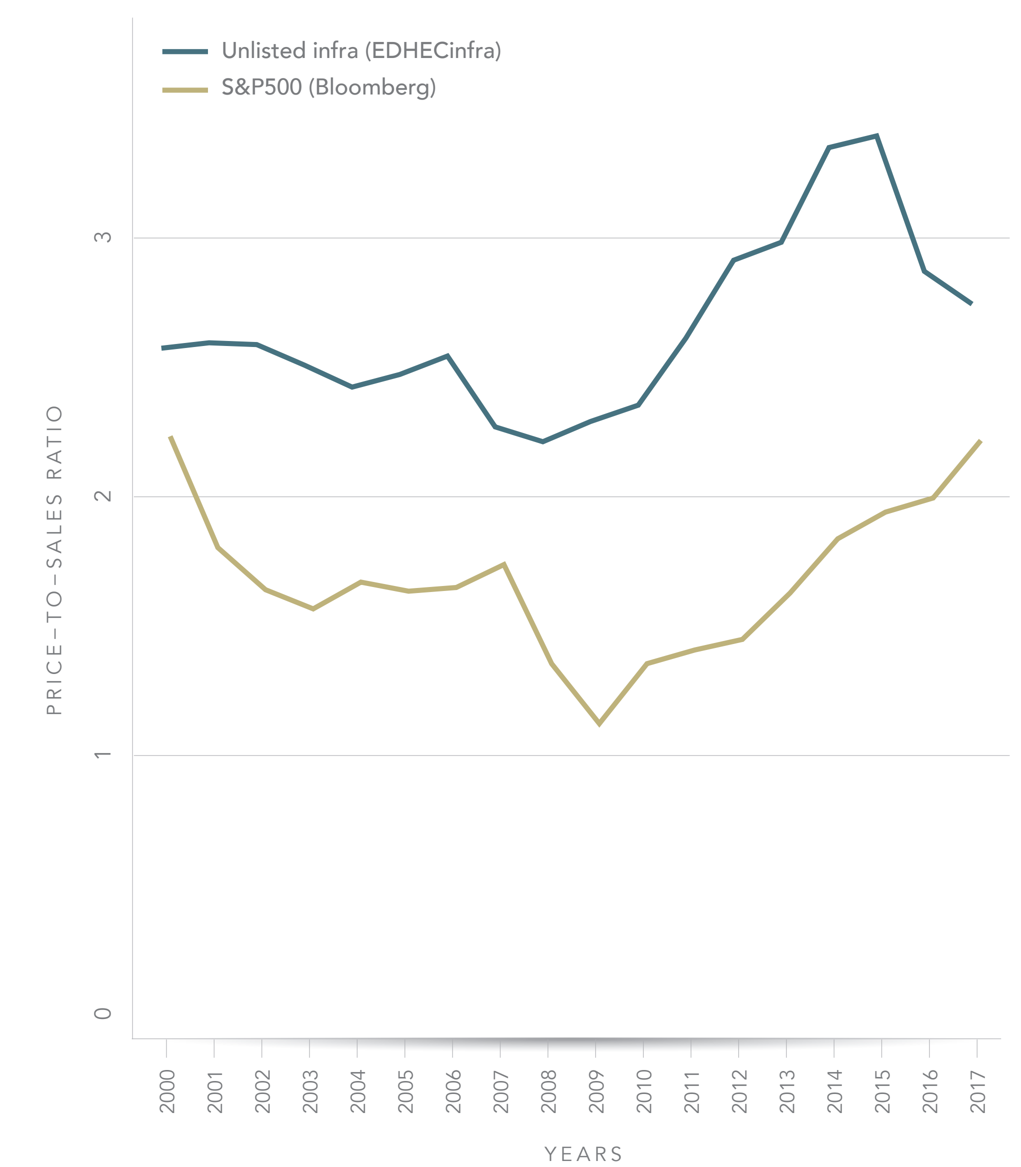
A second phenomenon documented in this paper is a shift to generally higher price regime of the unlisted asset class during the 2008-2015 period. During those years, the effect of certain risk factors on prices become less powerful, notably leverage, as average prices increase seemingly independently of their risk profile. During that period, the nature of investors active in the unlisted infrastructure market has also shifted: a period of price discovery (which has sometimes been called a bubble) led to lower required returns as the risk preferences of the average buyer of private infrastructure companies evolved. This period appears to end after 2015, when prices stabilize.

Infrastructure businesses are expected to deliver steady and predictable cash flows and to the extent that this is the case they should be expensive. Hence, after 10 years of price increases a price consensus may have been reached.

Unlisted infrastructure prices will, in all likelihood, continue to be driven by common factors in the future, while the evolution of investor preferences will also determine the general level of prices and of the fair value of the unlisted infrastructure asset class. Our results show that despite the evolution of investor preferences, systematic risk factors mostly continued to explain prices over that period, indicating that valuations remained, on average, rational and fair.

FIGURE 1

Mean price-to-sales ratio



Approach: from biased transaction prices to unbiased factor prices

One of the most important requirements of the IFRS 13 framework is to calibrate valuations to observable market prices. Private infrastructure is an illiquid market and assets do not trade often. As a result, observable transaction prices are limited and are not representative of the investible market. But the prices and returns of unlisted infrastructure equity can be expected to be driven by certain common factors, including some that exist in other asset classes and are well known.

To overcome this issue, we estimate the effect of six factors that impact observable transaction prices and apply these to the more representative EDHECinfra universe of unlisted infrastructure companies. We use statistical filtering techniques (Kalman filter) to capture the changing impact of these factors on prices over time as investor preferences and market conditions change. These factor effects are unbiased and statistically robust.

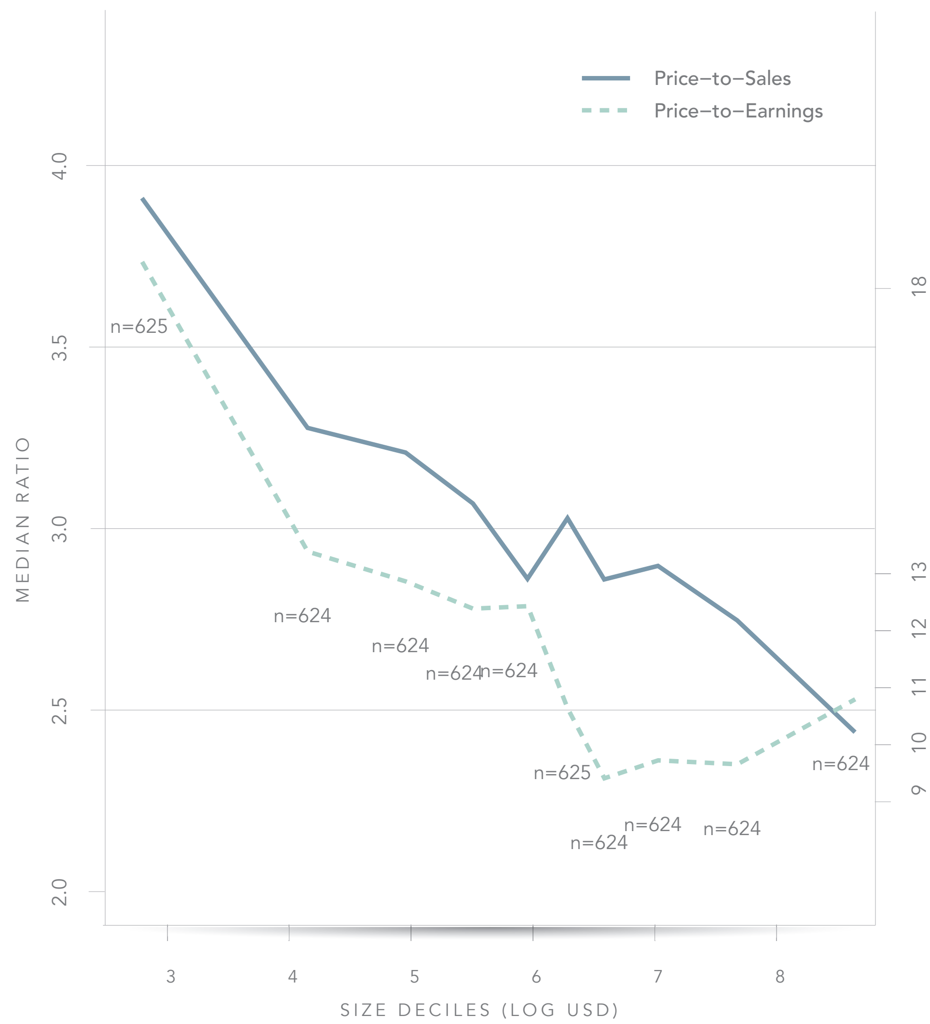
This allows us to compute thousands of "shadow prices" for those unlisted infrastructure companies that did not trade over the past 15 years. With this approach, we can document the price dynamics of the unlisted infrastructure market for the underlying population and not just for a biased sample of available transaction data.

[55] *"Which Factors Explain Unlisted Infrastructure Asset Prices?" - The EDHEC/Long-Term Infrastructure Investor Association Research Chair on Infrastructure Equity Benchmarking, 2016-2019*
http://edhec.infrastructure.institute/wp-content/uploads/publications/blanc-brude_and_tran_2019.pdf

We use a price-to-sales (PSR) ratio as a valuation measure, which reflects the willingness of an investor to pay for future risky revenue growth and dividends, adjusted for risk. We find that PSRs are well behaved statistically and present multiple advantages over price-to-book and price-to-earnings ratios, not the least that they always have a positive sign. A higher PSR indicates buyers are willing to pay more per dollar of average historical revenues, suggesting that these revenues are either expected to grow or considered more predictable. PSRs are also the standard metric used in international capital markets and may be compared directly with the equivalent ratio for public equity indexes.

FIGURE 2

Size versus Price-to-Sales and Price-to-Earnings



The six risk factors that explain unlisted infrastructure prices

1. Size: Previous research shows that small-cap stocks tend to outperform large-cap stocks because they have a higher exposure to systematic risk factors, undergo longer periods of distress in bad times, pose higher credit risk or are less liquid. In the case of infrastructure, larger assets are found to have lower prices i.e. higher returns. Effectively, size is a proxy of liquidity: larger infrastructure projects are more illiquid, complex to develop and the object of information asymmetries between buyers and sellers.

2. Leverage (credit risk): As for other firms, credit risk has an impact on equity investors in infrastructure, who take the risk of being 'wiped out' in the event of default. Infrastructure companies that have higher leverage – proxied by the ratio of total liabilities to total assets - thus have, on average, lower prices.

3. Profits: Also in line with theory, profitability impacts prices directly and positively. We find that the effect – proxied by the profit margin - is time varying and more important during bad times (the years following the financial crisis.)

4. Term spread: the value of infrastructure investments, with their high upfront capital costs, is determined by their long-term cash flows. They are therefore sensitive to interest (discount) rate changes. The term spread - the difference between long term and short-term interest rates – is found to have a negative impact on prices, also as theory predicts. In an international context, differences in term spread can also signal differences in country risk, especially when short-term rates are at the zero-lower bound, which is the case during most of the relevant period of observation.

5. Value: a value effect exists if companies are 'cheap' from one perspective or another. We look at infrastructure companies that report negative book values during their first ten years as a proxy of the 'value' period in their life-cycle. We find that the greenfield stage corresponds to a different level of prices than during the rest of the firm's life-cycle.

6. Growth: Infrastructure companies have limited growth opportunities as by nature they are designed to deliver individual investment projects with fixed revenues. Still, merchant infrastructure projects and corporates have opportunities to grow. For these companies, higher expected growth relatively increases prices. We also find that, in line with theory, realized revenue growth tends to have a positive effect on valuations.

Stylized facts: the dynamics of unlisted infrastructure prices

Price-to-sales ratios of infrastructure companies are significantly higher than in public markets, irrespective of market conditions. This reflects the ability of infrastructure companies to transform income into dividends, as highlighted in previous studies, pay-out ratios (dividend pay-outs over revenues) tend to be four to five times higher in mature unlisted infrastructure companies than in listed companies of equivalent size, leverage and profitability.

Price-to-earnings ratios tend to be much more volatile than in public markets. Indeed, pay-outs may be higher as share of revenues but they are also more variable as a result of the significant financial and operational leverage that characterizes infrastructure companies. Their large but mostly fixed production costs make any excess revenue a source of pure profit, but since any decline in revenues is not easily matched with a decline in production costs, profits can decline very fast as well.

For the most part, the factors driving unlisted infrastructure secondary market prices make sense: size, leverage, value or profitability have the signs predicted by theory and their effects are persistent, albeit variable, across time. This is significant to define an ex ante factor model of returns for the purpose of asset valuation.

Price formation and discovery is slow: the factor effects documented above can take several years to change from one level to another, as transactions and investor preferences are processed by market mechanisms. This is partly the reflection of unlisted infrastructure status as a 'new' asset class, so that numerous transactions were necessary over many years for 'fair' prices – representing the willingness to pay of numerous buyers and sellers at one point in time – to emerge. Prices do not react immediately to short-term variations in financial conditions: the swings in price-to-earnings are due to the fact that prices stayed on a steady increasing path for most of the period, while earnings swung up and down, especially in the merchant sector. This can be both a function of the slow processing of price information in a high illiquid market, as well as the reflection of the belief by buyers that most of the value of infrastructure companies is embodied in a long-term business model, which can be considered impervious to short-term volatility.

Valuations are not out of line with fair value: because price movements can be explained by systematic factors and the remaining variability of transaction prices appears to be idiosyncratic, prices can be said to have mostly evolved to reflect the preferences of market participants taking major risk factors into account. In other, words, pricing has remained rational and informed. The fact that prices have increased a lot over the past decade cannot simply be attributed to a 'wall of cash' effect in a market where many participants were chasing few available opportunities. •

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Pricing Private Infrastructure Debt

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Which factors explain private infrastructure credit spreads (and discount rates) and how do they evolve over time? Are infrastructure project finance spreads and infrastructure corporate spreads driven by common factors?

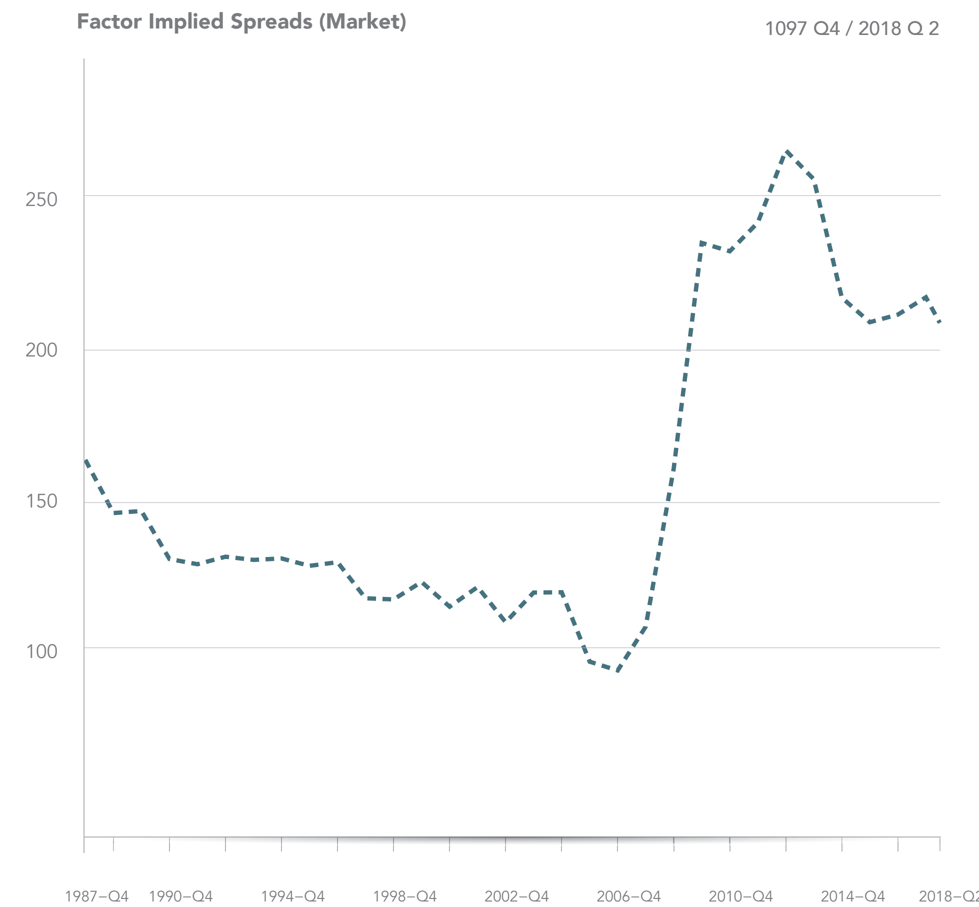
In new research supported by Natixis as part of the EDHEC/Natixis research chair on Infrastructure Debt Benchmarking, the EDHEC Infrastructure Institute (EDHECinfra) examines the drivers and evolution of credit spreads in private infrastructure debt.

We show that **common risk factors partly explain both infrastructure and corporate debt spreads.** However, the pricing of these factors differs, sometimes considerably, between the two types of private debt instruments.

We also find that **private infrastructure debt has been 'fairly' priced even after the 2008 credit crisis.** That is because spread levels are well-explained by the evolution of systematic risk factor premia and, taking these into account, current spreads are only about 20bps above their pre-2008 level. In other words, taking into account the level of risk (factor loadings) in the investible universe and the price of risk (risk factor premia) over the past 20 years, we only find a small increase in the average level of credit spreads, whereas absolute spread levels are twice as high today as they were before 2008.

FIGURE 1

Input/output spreads over time



A better approach to estimating market credit spreads

The main difficulty facing econometric research on the pricing of infrastructure debt is the paucity and biases of observable data. Secondary transactions are very rare and usually not instrument-level sales. Still, large number of primary transactions (at the time of origination) can be observed. Nevertheless, this data is biased: origination follows procurement and industrial trends e.g., it tends to cluster in time and space when and where governments procure new infrastructure using a privately-financed model. Simply observing origination credit spreads over time does not take into account the underlying market for private infrastructure debt to which investors are exposed.

Primary spread data is also auto-correlated i.e. what best explains the spread for a given infrastructure borrower is not its characteristics, but the spread of the previous transaction.

To address these issues and estimate the effect of individual risk factors on spreads we do two things. Firstly we estimate the evolution over time of the risk factor premia and determine their unbiased effects on spreads over time. Secondly we use the EDHECinfra universe, a representative sample of existing infrastructure borrowers – as opposed to the biased sample of new borrowers in the primary market – to apply the risk premia estimated in the first step to the 'factor loadings' (the characteristics) of this better sample, thus computing a current market spread for each one, at each point in time.

Using a factor model in combination with a representative sample of investible assets can correct the bias and paucity of available data: as long as such factors can be documented in a robust and unbiased manner, they can be used to assess the fair value of private debt investments over time, whether they are traded or not.

What factors explain infrastructure credit spreads?

Our results show how the aftermath of the 2008 crisis changed and sometimes removed well-established relationships between certain factors and the cost of corporate and infrastructure debt: the impact of base rates on loan pricing disappeared, structural differences between markets vanished and certain sectors like roads experienced a continued increase in the price of long-term private financing.

Our results are statistically robust and explain the data well. We show that infrastructure and corporate credit spreads are determined by a combination of common factors that can be grouped into four categories:

1. Market Trend: the largest effect driving credit spreads in both infrastructure and corporate debt is a time-varying trend factor which captures the state of the credit market over time. This effect is not explained by loan or borrower characteristics. In the case of infrastructure debt, this effect is roughly constant but exhibits "regime shifts", especially 2008 (up) and 2014 (down). In the case of corporate debt, it is an upward trend also exhibiting jumps in 2008 and 2012. We find a 20bps increase of infrastructure spreads compared to pre-crisis levels, down from 75bps at the height of the credit crisis, indicating a degree of mean-reversion.

2. Credit Risk only explains part of the level of credit spreads. We find that infrastructure borrowers that are exposed to Merchant Risk are required to pay a time-varying premium from 20 to 40% above the market average at the time. Size has no effect on average corporate spreads but is a driver of lower risk premium in infrastructure debt. In effect, larger loans can be interpreted as a signal of lower credit risk in infrastructure finance. Industrial groups can considered be a partial proxy for credit risk but are mostly not significant, expect for social infrastructure and, amongst corporate borrowers, infrastructure corporates, which have come to benefit from a substantial discount relative to average market spreads in recent years.

3. Liquidity: Other drivers of spreads are proxies of the cost of liquidity for creditors. Maturity: while it is difficult to capture in static models, maturity is found to be a significant and time-varying driver of spreads for corporate debt, with higher premium charged during period of lower bank liquidity (2008-2016), whereas infrastructure debt has a constant maturity premium. While the effect of size is primarily a matter of credit risk, we note that in periods of limited creditor liquidity (2008), even infrastructure debt becomes more expensive as a function of size. However, this effect is not strong enough to create a size premium.

Re-financings, which are not a significant driver of spreads in normal times, are shown to be more expensive in times of credit market stress, especially for infrastructure debt.

4. Cost of Funds: the benchmark against which floating rate debt is priced has been a factor explaining the level of credit spreads. Base rates are inversely related to spread i.e. higher rates imply lower spreads, but this effect is shown to have all but vanished since 2008. Since then, the level of credit spreads and that of base interest rates has become completely uncorrelated. Market Segments: taking base rates into account, some markets are cheaper than others as a result of the well-known segmentation of credit markets. This is the case when comparing Libor- vs-Euribor-priced loans but also the different geographic areas in which different lenders operate. Again, since 2008, these differences have tended to disappear.

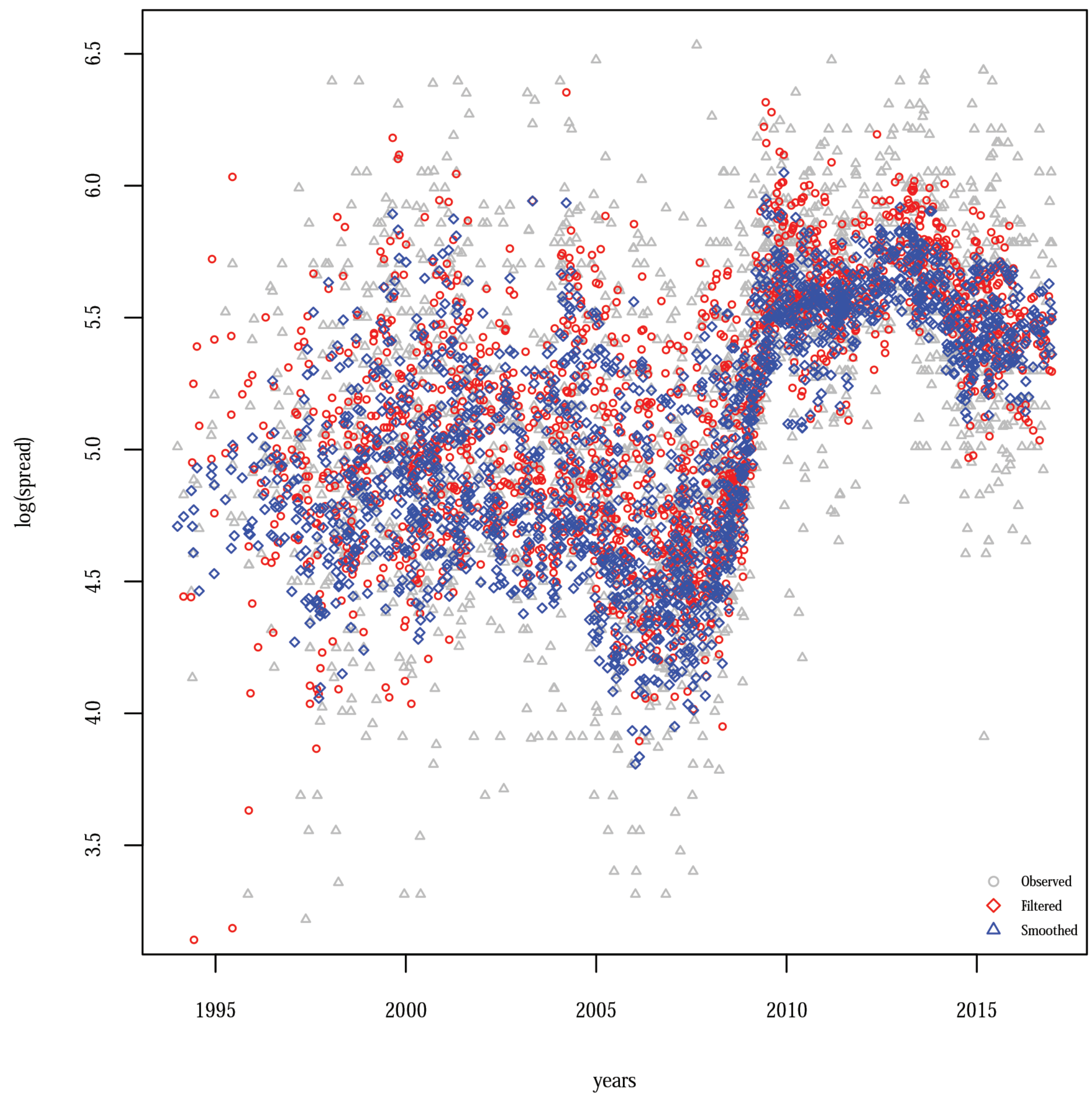
Towards fair value in private infrastructure debt

Our assessment of the impact of certain risk factors in the formation of aggregate credit spreads is relevant for at least three reasons:

- While observable spreads are biased due to the segmentation and low liquidity of the private credit market, unbiased factor prices (premia) can be estimated from observable spreads, and used to determine the factor-implied spreads for any instrument at any time;
- The time-varying nature of individual risk premia implies that re-pricing individual instruments over time can be material and is required if such investments are to be evaluated on a fair value basis;
- A multi-factor model of spreads i.e. discount rates, allows more robust valuation taking into account the effect of systematic risk factors. One of the most important requirements of the IFRS 13 framework is to calibrate valuations to observable market prices, thus ensuring that estimated spreads represent current investor preferences at the measurement time. While fair value is not always required for debt instruments, which are booked at their face value unless they become impaired, the requirement to evaluate assets on a like-for-like basis will only grow as the private debt asset class becomes a more significant part of investors' portfolios. •

FIGURE 2

Infrastructure Debt: Observed and Predicted Spreads



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REFERENCES
• ***Blanc-Brude, F. and J-L Yim,*** *Forthcoming, "The Pricing of Private Infrastructure Debt" EDHEC Infrastructure Institute – Singapore Publication.*