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With an average annual excess return of 2.47% and an 57.07% improvement in risk-adjusted performance observed over the long run* in comparison with traditional factor indices, ERI Scientific Beta’s smart factor indices are the essential building blocks for efficient risk factor allocation.

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


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INTRODUCTION

Noël Amenc
Associate Dean for Business Development,
EDHEC Business School, CEO, ERI Scientific Beta

It is my pleasure to introduce the latest “Scientific Beta” special issue of the 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.

Even though gaining explicit exposure to priced risk factors in the equity space is expected to provide good long-term risk-adjusted performance, investing in these factors also exposes the investor to a number of hidden or implicit risks that could be important drivers of short-term performance. In our article, we document and gain a better understanding of these hidden risks.

We assess the investability of smart beta equity strategies, as they naturally incur additional implementation hurdles compared to cap-weighted indexes. While there are different dimensions related to investability, such as liquidity, capacity and transaction costs, it is possible to provide transparency on these dimensions with a range of metrics developed in market microstructure research. Our article introduces a suite of analytics to enable investors to assess the investability of smart beta indexes.

Multi-factor index providers have been debating the respective merits of the “top-down” and “bottom-up” approaches to multi-factor equity portfolio construction. We review general insights from the literature on return estimation and factor models that are relevant for multi-factor portfolio construction and discuss recent literature that specifically addresses issues with bottom-up portfolio approaches.

In an article drawn from the Amundi ETF, Indexing and Smart Beta Investment Strategies research chair at EDHEC-Risk Institute, we clarify the various possible definitions of factors that are relevant in investment practice and develop a framework for allocating to factors in two main contexts, namely allocation decisions at the asset class level, and benchmarking decisions within a given class. It is possible to use factor indexes as building blocks and to diversify risk across underlying factors, or to seek to exploit knowledge of economic regimes to design portfolios that react to changes in market conditions.

Goal-based investing principles can be used to effectively address the retirement investing problem by allowing investors in transition to secure minimum levels of replacement income for a fixed period of time in retirement, and also generate the kind of upside needed to reach target levels of replacement income with attractive probabilities. The emergence of the goal-based investing paradigm has effectively allowed for the development of mass-customized investment solutions to individuals. Risk management will play a central role in what should be regarded as nothing short of an industrial revolution that is impacting the investment management industry.

Being able to estimate the risk premium attached to Treasury bond yields in a reliable and robust manner is key to successful investing. EDHEC-Risk Institute has therefore launched the ERI Risk Premium Monitor: a robust tool to derive a state-of-the-art estimation of the risk premium using market and monetary-policy information. Our article explains how this task is achieved and the theoretical underpinnings of the analytical tools used for the task.

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.
Improving Risk Disclosure in the Smart Beta Space

Eric Shirbini
Head of Applied Research,
EDHEC-Risk Institute, Research Director,
ERI Scientific Beta

INTRODUCTION

A recent EDHEC Survey on Equity Factor Investing (Amenc et al., 2017a) highlights that one of asset owners’ primary motivations for investing in smart factors was to replace costly active managers with indexes representative of a choice of factors that are well-rewarded over the long term. In addition to providing access to well-rewarded risk factors at a lower cost compared to active managers, the asset owner also benefits from having much greater transparency and explicit control over which well-rewarded factors to invest in. Unfortunately, more often than not, the decision of which single- or multi-smart-factor index to invest in is made simply on the basis of the lowest cost and recent performance. However, by making an explicit choice over which factors to invest in, the asset owner now also takes on the fiduciary responsibility of their investment choices, which in the past had been delegated to the asset manager. Most of the performance and “alpha” of asset managers came from implicit factor choices, as was well documented in Ang et al.’s report for the Norwegian Government Pension Fund in 2009. Investing in smart beta requires the asset owner to understand the consequences of making this investment decision. Even though gaining explicit exposure to priced risk factors (such as size, value, momentum, low volatility or quality) is expected to provide good long-term risk-adjusted performance, investing in these factors also exposes the investor to a number of hidden or risks that could be important drivers of short-term performance.

• Even though gaining explicit exposure to priced risk factors is expected to provide good long-term risk-adjusted performance, investing in these factors also exposes the investor to a number of hidden or risks that could be important drivers of short-term performance.
• Documenting such risk exposures is crucial to reconcile them with investors’ preferences. With the calling into question of the default option that the cap-weighted index represented as a passive investment reference, smart beta’s main fiduciary message is that there is no best solution in general, but instead a best solution that allows the investor’s fiduciary choices to be executed in the most efficient way. Ultimately, the choice on managing these risks is a key fiduciary decision that cannot be left to the appreciation of an index provider who has no status to do so.
• Asset owners’ governance practices should also be improved by starting a risk conversation on smart beta investments with stakeholders.

Impact of Market Beta on Performance

Universe is EDHEC Risk U.S. Long Term Track Records. Time period of analysis is from Dec. 31, 1975, to Dec. 31, 2015 (40 years). The analysis is based on weekly total returns in USD. All statistics are annualized. Yield on 30-year U.S. Treasury Bills (US) is used as a proxy for the risk-free rate. The Market factor is the excess return series of the cap-weighted index over the risk-free rate. The other six factors are equal weighted daily rebalanced factors obtained from Scientific Beta. Coefficients significant at 5% p-value are highlighted in bold.

<table>
<thead>
<tr>
<th>Factor</th>
<th>Exposure</th>
<th>Performance Attribution</th>
</tr>
</thead>
</table>
| Ann. Unexplained | 1.92% | Ann. Unexplained 2.99%
| Market Beta | 0.97 | Market Factor 5.71%
| SMB Beta | 0.18 | SMB Factor 0.34%
| HML Beta | 0.14 | HML Factor 0.01%
| MOM Beta | 0.04 | MOM Factor 0.17%
| Low Vol Beta | 0.14 | Low Vol Factor 0.22%
| High Prof. Beta | 0.09 | High Prof. Factor 0.19%
| Low Inv. Beta | 0.07 | Low Inv. Factor 0.18%

Interaction with other asset classes included in the policy benchmark, leading to a potential misalignment with the objectives of the policy benchmark. One of the key conclusions of the seminal study by Ang et al. (2009) of the Norwegian Government Pension Fund was to consider a framework that more explicitly recognizes the structure of its return-generating process via investment in factor benchmark portfolios that go beyond asset classes. A better model of diversification is to diversify across these factors rather than relying on asset class diversification. In such a framework it is important to recognize an implicit risk such as exposure to interest rate risk, which may already be present in the fixed income part of the portfolio, by investing explicitly in a low volatility equity factor. Lastly, unveiling these hidden or implicit risks also leads to better governance. A key question for investors is how to evaluate and communicate on the risks of their smart beta investments with respect to the different stakeholders. Ang and Kjaer (2011) note that “a thorough understanding by the asset owner of the key factor drivers of risk and return... is the best way to counter” governance problems. An explicit choice of equity factors by asset owners naturally improves governance, compared to implicit choices made by active managers. However, equity factors themselves lead to other implicit risks, which need to be documented. For example, an explicit choice to get value exposure may lead to unintended macroeconomic risks (since value tends to do poorly when the term spread or industrial production declines and this type of macroeconomic risk is very different depending on the country). Popular minimum volatility strategies tend to result in counter-cyclical exposure because these strategies overweight health care and underweight energy stocks by about 5% compared to the market index. Just like monitoring the style drift of active managers, investors need to monitor the risk dynamics of factor strategies. In addition, a strategy with constant exposure to value may have time-varying market betas, because, like the momentum factor, this strategy exhibits strong variations in market beta. These variations naturally have strong consequences on the out-of-sample performance of the strategy and more globally on their conditionality. This subject of the implicit market
beta bet taken by factor strategies is probably one of the most poorly documented points in the academic literature devoted to factors, as shown by Amenc et al. (2018).

Mind the market beta gap

The primary focus of the vast majority of providers of multi-factor strategies is on improving factor intensity in the hope of benefiting from higher premia in the long term. There is much debate on the best way to improve the performance associated with these factor exposures. In the same way, the question of improving factor intensity in the case of multi-factor assemblies has given rise to extensive literature. Amenc et al. (2017b, 2017c) published two important contributions on this subject in 2017. However, little attention is paid to the management of market beta in such multi-factor strategies. This may be surprising because, while it is obviously important to consider exposures to factors other than the market, one also needs to recognize that the market exposure heavily conditions the performance of multi-factor strategies. The market beta of smart beta strategies is an implicit result of various construction choices but most smart beta offerings have a market beta that is uncontrolled and often lower than one due to the defensive bias of some factors and weighting schemes. This market beta, if left uncontrolled, can lead to significant biases in performance and such biases are often left undocumented. The first order question (of market risk exposure) is ignored while the second order question (of factor intensity) has taken center stage.

Biases introduced by leaving the market beta of smart beta strategies unmanaged can have two adverse consequences. Firstly, the strategy could be losing out on the long-term equity market risk premium which accounts for a significant portion of long-term performance of any long-only equity strategy. Defensive smart beta strategies with a market beta of less than one lose out on some of this market risk premium (but this performance obviously also comes with lower risk). Secondly, uncontrolled market risk exposure can also produce pronounced differences in short-term performance since market exposure heavily influences the conditional performance of multi-factor strategies. Defensive factor strategies will tend to underperform in bull markets but strongly outperform in bear markets, whereas aggressive factor strategies tend to outperform in bull markets but underperform in bear markets. It is thus crucial to document market beta biases to be able to reconcile them with investor preferences and to correct them, if necessary. Ultimately, the trade-off posed by many multi-factor strategies between a possible reduction in outperformance potential and a strong reduction in volatility, which leads to a clear improvement in the Sharpe ratio over the long term, should be made explicit and should be validated by the stakeholders in the investment.

The importance of market exposure for the performance of smart beta strategies is readily observable from a factor performance attribution analysis of such strategies. As an illustration, Exhibit 1 shows the factor exposures (betas) and performance attribution of the EDHEC-Risk U.S. Long-Term version of Scientific Beta’s flagship U.S. High-Factor-Intensity Multi-Beta Multi-Strategy Six-Factor EW index, which is constructed by equally weighting a combination of six single-factor tilted sub-indexes. These sub-indexes are designed to be exposed to the size, value, momentum, low volatility, high profitability and low investment factors. A diversified weighted scheme is used to construct each sub-index. We regress the returns of the multi-factor strategy on a 7-factor model that includes the market factor and six targeted factors to obtain the factor exposures.

The importance of the market exposure of the strategy is clearly documented in Exhibit 1. The results of this regression show that the multi-factor index indeed has statistical and significant exposure to all six targeted factors and an exposure of 0.97 to the market factor. It is interesting to see that the exposure to the market factor is responsible for 5.71% annualized returns, i.e., more than half of the performance of the strategy. The impact of other factors is much smaller. The size exposure contributes 0.34% of the performance, while the momentum, value and profitability exposures contribute 0.09%, 0.07% ,and 0.04%, respectively.

1 “Accounting for Cross-Factor Interactions in Multi-Factor Portfolios: the Case for Multi-Beta Multi-Strategy High Factor Intensity Indices” and “Why we do not Believe that Maximizing Factor Intensity at Stock Level is a Robust Approach to Multi-Factor Investing.” See references for full details.
low investment and high profitability factors contribute about 0.17%-0.19% of the returns each. Therefore, properly accounting for market beta in evaluating, selecting, and implementing smart beta strategies is imperative for sound decision-making with respect to such strategies. In fact, the cost of deviating from a market beta of one can be estimated in a straightforward fashion. In Exhibit 2, we report the cost of being underexposed to the market for the EDHEC-Risk U.S. Long-Term version of Scientific Beta's High-Factor-Intensity Multi-Beta Multi-Strategy 6-Factor EW Index. Exhibit 2 illustrates the different components of performance. The multi-factor strategy generates a positive return in excess of what is explained by its market exposure. This component is what motivates smart beta investors to pursue the strategy, and is driven by better diversification and better factor tilts of the strategy, relative to the cap-weighted market index. However, at the same time, the strategy has lower market exposure than the cap-weighted market index, which leads to a cost of under-exposure. This cost is given by the difference in market beta of the multi-factor strategy less a market beta of one, multiplied by the long-term market premium. The multi-factor strategy gives up market exposure (by an amount $\Delta \beta$), which results in giving up market returns. The cost of this under-exposure is more than offset by the higher returns generated by the other components of the strategy. The market exposure of the strategy also has an even more important impact on the return variability of the multi-factor index. Exhibit 4 shows a risk attribute analysis of the multi-factor strategy. The volatility contribution of the market factor is 17.55%, while each of the other six factors contributes less than 0.5%.

Not only is the market factor a strong contributor to the overall risk of a long-only multi-factor allocation, but the market beta is also highly time varying. Exhibit 5 shows two-year rolling market betas (from a CAPM model) of U.S. Long-Term dollar-neutral long/short factors from Scientific Beta. Dollar-neutral long/short factors are typically used to control market betas since the market exposure of the long/short is mitigated by the market exposure of the short leg. Exhibit 5 shows that the factors’ market betas are highly variable, and this variability is expressed strongly even in a long/short framework. Some factors like low volatility and low investment are associated with negative CAPM beta but the variation in the magnitude of beta is quite high. The other four factors show both positive and negative CAPM beta depending on the period, with momentum showing rather cyclical behavior. During bull periods, the market factor loads on high-market-beta stocks and during falls in the market, it is exposed to low-market-beta stocks as these stocks are the least badly hit in terms of performance. Daniel and Moskowitz (2016) also show that momentum-tilted portfolios tend to rebalance to low (high) beta stocks following periods of low (high) market returns. The impacts of this variation in beta on the conditionality of performance are considerable, especially since the factors’ market betas can have poor conditional qualities. The negative consequences of highly conditional market betas of factors can be corrected by making the factors beta-neutral. The CAPM betas are calculated over a long period of the long and short legs of dollar-neutral long/short (L/S) factors is used to leverage/de-leverage the long and short legs to beta 1.

Exhibit 6 compares the extreme conditional performance of the six U.S. long-term long/short factors in dollar-neutral form and in a form that controls for the market beta (statically beta-neutral form). The low volatility and low investment factors, which have negative market exposure in dollar-neutral form, exhibit poor performance in extreme bull markets and good performance in extreme bear markets. This is a direct consequence of their negative exposure to the market factor. The statically beta-neutral factors correct this conditional performance asymmetry. From an investor’s perspective, the dependency of the (uncontrolled) factors on market conditions leads to an implicit exposure that may not be desirable. In the case of the value factor, for example, we observe that the uncontrolled factor generates profits in bear markets while generating losses in bull markets. However, the motivation for gaining value exposure is definitely not to make implicit bets on the market but rather to harvest the value premium. Therefore, a relevant question is how to implement factor exposures while controlling market exposure.

Given the importance of the market risk factor, it seems surprising that — up until now — the market risk for the vast majority of multi-factor offerings had not been managed. In fact, while there have been heated debates about which precise definition to use for non-market factors (see for example Blitz et al. (2011) or Rao et al. (2015) among many others), whether or not such factors are overpriced (see the debate in Arnott (2016) and Asness (2016)), and how to control the intensity of exposure to such non-market factors (see Benders and Wang (2016) or Clarke et al. (2016), among many others), there has been little, if any, discussion on controlling market risk. Indeed, one might argue that, in focusing on the second order question (of the exposure to factors other than the market), smart beta providers have neglected the first order question (exposure to the market factor).

Hidden macro sensitivities

Factor strategies are also exposed to macroeconomic risks, something investors may not be aware of, as they are not documented by most providers. Biases in macro sensitivities will also impact performance similar to market risk bias. Factor sensitivities to macroeconomic risks lead to different performance in different macro conditions. More importantly, macro exposure biases will lead to interaction effects with other factors and other asset classes. For example, strategies with sensitivity to credit risk or interest rate risk will interact with fixed-income portfolios. A multi-factor portfolio may lack diversification across factors if several risk factors are sensitive to the same macro driver. In this case, having a constant and balanced (beta) exposure to multiple rewarded risk factors may not necessarily improve the diversification of the portfolio. Focusing instead on the diversification of the factor risk premia within a macroeconomic regime is more important than maintaining a balanced exposure across multiple factors. In this section, we illustrate the macro sensitivities of equity factors to a set of relevant macro-variables.

We will assess the conditional performance of six well-known long/short equity risk factors conditioned upon various macroeconomic variables. Calendar months are sorted into quartiles according to each conditioning variable, and
monthly average returns are compared. For the sake of brevity, we only report spreads between extreme quartiles. For example, in the case of inflation, the reported figure will correspond to the difference in average monthly returns between 25% of calendar months when inflation was highest vs. lowest. We use EDHEC-Risk Long-Term Track Records over the past 40 years. The macroeconomic variables that the returns of the factors are conditioned on can be broadly grouped into four categories and are shown in Exhibit 7.

Exhibit 8 shows the conditional performance of the six long/short factors using the EDHEC-Risk U.S. Long-Term Track Records (Dec. 31, 1975 to Dec. 31, 2015). Some factors reveal opposite sensitivity to a number of macroeconomic variables, suggesting there is room for offsetting sensitivity to macroeconomic variables by suitably designed factor combinations. For example, size and low volatility have complimentary exposure to several macroeconomic variables and value and momentum have strong complimentary sensitivity to changes to term spread.

The sensitivity to macro variables is most pronounced for the low volatility factor, and the size factor was also influenced by a large number of conditioning variables. Value and high profitability were the least dependent factors to the selected variables. Most factors were sensitive to sector spread and change in dividend yield, while industrial production, inflation and liquidity had no influence on factor premia.

Part of the sensitivity of factors to macroeconomic variables may be due to non-zero market exposures of the long/short factors. If the market is sensitive to the conditioning variable, and if the given factor is exposed to market risk, analysis may confound market exposure and macro exposure. To eliminate the market effect, in Exhibit 9 we look at the CAPM alpha instead of absolute returns.

Exhibit 3 shows the low volatility and low investment factors are no longer sensitive to market returns and dividend yield after adjusting for market exposure, but still negatively exposed to the sector spread. The size, value and momentum factors respond in a similar way to the different macro variables after controlling for market beta. Again, the high profitability factor appears as the least responsive to macroeconomic variables.

Overall, we see that the difference between factor returns in different regimes is partly driven by market exposure. This strong difference in the macroeconomic conditionality of market-beta-adjusted vs. non-market-beta-adjusted factor strategies has important consequences, notably when it involves qualifying factor regime premia and trying to predict the future returns of the factors associated with these premia. Many long-only active managers who are opposed to the difficulty (impossibility) of producing alpha in traditional tactical allocation are just repackaging doubtful market return forecasting skills as new factor timing skills. This difficulty stems from the complexity in predicting future market returns with the expected robustness of factor regime premia forecasting (forgetting that a large share of the observed conditionality of factor returns is in fact related to market beta).

Exposure to sector and country-specific risks

Managing unquestioned risks is one of the key challenges faced by smart beta investors. Index providers are not always transparent about the implicit unrewarded bets their offerings are exposed to. Sector and region effects are important in explaining the variation in stock returns per se, but these are unquestioned risks over the long term and therefore have to be validated by investors, because there is no empirical or academic evidence for taking these risks.

Exhibit 10 shows smart beta strategies can lead to strong biases compared to the cap-weighted benchmark, if left unmanaged. These biases often have more impact on performance in the short and medium term than the risk premium associated with low volatility over the long term.

In addition, though investors are often encouraged to look at the factor intensity alone as an explanation for good back-tested performance, it should be stressed that the way in which one obtains this factor intensity is not neutral from the perspective of exposure to unquestioned risk. In our view,

<table>
<thead>
<tr>
<th>Group</th>
<th>Variable</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stock Market Indicators</td>
<td>Market Returns</td>
<td>Returns on Scientific Beta cap-weighted market index. Source: Scientific Beta.</td>
</tr>
<tr>
<td></td>
<td>Change in Market Volatility</td>
<td>Standard deviation of daily returns on Scientific Beta cap-weighted market index computed monthly. Source: Scientific Beta.</td>
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<tr>
<td>Economic Indicators</td>
<td>Industrial Production Growth</td>
<td>The Industrial Production Index (INDPRO), seasonally adjusted: Source: Board of Governors of the Federal Reserve System (U.S.).</td>
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<tr>
<td></td>
<td>Sector Spread</td>
<td>Defined as a difference between returns on Cyclical and Defensive Sectors, according to MSCI classification. Source: MSCI.</td>
</tr>
<tr>
<td></td>
<td>Inflation</td>
<td>Returns on a seasonally adjusted Consumer Price Index have been used as a proxy for inflation. Source: U.S. Bureau of Labor Statistics.</td>
</tr>
<tr>
<td></td>
<td>Change in Aggregate Traded Volume</td>
<td>Defined as a ratio of total daily dollar volume traded in the universe over aggregate market capitalization of the universe in USD.</td>
</tr>
<tr>
<td>Asset Pricing Indicators</td>
<td>Change in Term Spread</td>
<td>Defined as a difference between yields on 10-year and 1-year government bonds. Source: U.S. Treasury Yield Curve.</td>
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<tr>
<td></td>
<td>Change in Default Spread</td>
<td>Defined as spread between Moody’s AAA and BAA corporate bonds. Source: Moody’s Investors Service.</td>
</tr>
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<td></td>
<td>Change in 12-Month Dividend Yield</td>
<td>Defined as the difference between log returns of total return index and price index of broad cap-weighted index. Source: U.S. Treasury Yield Curve.</td>
</tr>
<tr>
<td>Other Asset Classes</td>
<td>Sovereign Bond Returns</td>
<td>Returns on Barclays U.S. Treasury Bond Index have been used as a proxy for sovereign bond returns. Source: U.S. Treasury Yield Curve.</td>
</tr>
<tr>
<td></td>
<td>Currency Returns</td>
<td>Broad trade-weighted USD Index is used as proxy. Source: Board of Governors of the Federal Reserve System (U.S.).</td>
</tr>
</tbody>
</table>

Exhibit 4 shows that the long/short factors are indeed very long/short by construction. The spread factor is the most extreme, followed by the value factor. The low volatility and size factors also have significant skewness.

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Exhibit 6 shows how factor exposure is related to factor returns. The long/short factors are indeed highly correlated with each other, with some even perfect correlation. This can be explained by the fact that the long/short factors are constructed to maximize the difference in returns between the long and short portfolios. The high correlation among the long/short factors can also be seen in Exhibit 9, where the CAPM alphas are highly correlated.

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In addition, though investors are often encouraged to look at the factor intensity alone as an explanation for good back-tested performance, it should be stressed that the way in which one obtains this factor intensity is not neutral from the perspective of exposure to unquestioned risk. In our view,
it is a shame not to document this subject from the viewpoint of the fiduciary responsibility of the investor or their asset manager. Exhibit 11 shows that bottom-up approaches to multi-factor portfolio construction may be influenced substantially by sector biases. Naturally, documenting does not necessarily mean neutralizing. For example, there is no orthogonality between factor tilts and sector tilts, which are both microeconomic bets. A sector-neutrality constraint necessarily reduces the factor intensity, which reduces absolute risk-adjusted return over the long term but comes with better control of tracking error, which may be desirable for investors whose performance is measured relative to a cap-weighted benchmark and are more concerned about relative risk-adjusted return. On the other hand, if the objective of the factor strategy is to achieve high absolute risk-adjusted returns or if the objective of the investor is to benefit from diversification across factor premia with opposing sensitivity to a sector spread, it will not be a good idea to limit this cyclical by imposing sector constraints. For these reasons, ERI Scientific Beta, which positions itself as an index provider that leaves the choice of fiduciary options to those who have real responsibility for them, offers its multi-factor indexes with and without sector neutrality as a risk control option depending on the requirements of the investor. Comparing the performance of such indexes with and without sector control allows documenting the importance of sector risks.

In the same way, smart beta strategies correspond too frequently to optimisations at the stock level that do not take the geographical risk into account. This risk is not “naturally” re-warded and should therefore be subject to an explicit decision. Exhibit 12 shows that smart beta strategies can lead to strong regional biases compared to the cap-weighted benchmark.

Unlike sector risk, there is no real and serious trade-off here between taking justified macroeconomic and microeconomic risks. Taking macroeconomic risks on the basis of academic reasoning and for bets that correspond to a pure microeconomic dimension makes no sense and is ultimately disrespectful to the stakeholders in the investment. ERI Scientific Beta suggests neutralizing these risks at the regional level consistently on the basis of respecting the relative weight in market capitalization of each region. This regional approach reconciles smart beta and factor investing and controls unwarranted geographical risks. Factor investing has been documented to work best when performed within economically-integrated regions. Following the rejection of the global model by Griffin (2002), Fama-French (2012) build regional models that support index construction at the block-level. There is no justification for using microeconomic factors to take macroeconomic bets. ERI Scientific Beta offers its single and multi-factor strategies also on a regional basis, allowing an investor to take active regional bets.

Finally, one should note that unlike in developed world regions, countries within emerging market regions are not as highly integrated, and Exhibit 13 shows that factor indexes may display large deviations in country exposures compared to the cap-weighted benchmark.

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Finally, one should note that unlike in developed world regions, countries within emerging market regions are not as highly integrated, and Exhibit 13 shows that factor indexes may display large deviations in country exposures compared to the cap-weighted benchmark.

Exhibit 14 shows these large deviations in country exposures lead to high relative risk and low information ratios. Controlling for country risks (geo-neutral) reduces tracking error and maximum relative drawdown and leads to an improvement in the information ratio compared to the non-country-neutral version. Here a very clear decision needs to be taken between the search for a better Sharpe ratio over the long term, which authorizes the control of factor investing at the country level, vs. the better management of conditionality and relative risk with respect to reference cap-weighted indexes that the country-neutral option allows.

### Exposure to Sector Biases

The table reports sector allocation and relative allocation as of Dec. 16, 2016. The relative allocation is difference in allocation of the index and MSCI World. The allocation of MSCI World and MSCI World Min Vol is approximated using ETFs (iShares MSCI World UCITS ETF and iShares MSCI World Minimum Volatility UCITS ETF, respectively). The table reports sector allocation and relative allocation as of Dec. 16, 2016. The relative allocation is difference in allocation of the index and MSCI World. The allocation of MSCI World and MSCI World Min Vol is approximated using ETFs (iShares MSCI World UCITS ETF and iShares MSCI World Minimum Volatility UCITS ETF, respectively). The average returns from the bottom to top quartiles are increasing/decreasing monotonously. The most influential variable across each factor is highlighted in red font.
CONCLUSION

Smart beta investors are subject to several risks that most providers fail to report on reliably. These undocumented risks can have a significant impact on performance. Documenting such risk exposures is crucial to reconcile them with investors’ preferences. With cap-weighted indexes, which represent the default option in terms of a passive investment reference, being increasingly called into question, smart beta’s main fiduciary message is that there is no best solution in general, but rather a best solution that allows the investor’s fiduciary choices to be executed in the most efficient way. This is probably what best defines the difference between passive investment and active investment at a time when the former is no longer static and brings its own promise of outperformance compared to the cap-weighted index.

Future challenges for smart beta index providers are to address fully the implications of smart beta risk exposures. An industry-wide effort is needed to improve disclosure of risks. Every risk is an opportunity (for risk management). Documenting all the risks is a necessary condition for managing those risks through new innovative solutions. Ultimately, the choice on managing these risks is a key fiduciary decision that cannot be left to the appreciation of an index provider who has no status to do so.

Asset owners’ governance practices should also be improved by starting a risk conversation on smart beta investments with stakeholders. Which risks are desired and undesired? How to align risks with investment beliefs? How to evaluate and manage interaction across the policy portfolio?

Finally, one should note that unlike in developed world regions, countries within emerging market regions are not as highly integrated...
Asset owners’ governance practices should also be improved by starting a risk conversation on smart beta investments with stakeholders.

References

I N T R O D U C T I O N

With the advent of smart beta equity indexes, which represent alternatives to market-cap weighted indexes, a major question about their investability has been raised: at what cost will investors be able to trade the index constituents in the same proportions as the underlying strategy? In fact, departing from the traditional cap-weighting investment scheme leads to risks that are sizable and significantly different, as shown in Amenc, Golz and Lodh (2012) and Amenc, Golz and Martellini (2013). These include common exposures to systematic risk factors such as size and liquidity.

Also, in contrast to cap-weighted indexes, which are deemed to be buy-and-hold investments, and which are only marginally reviewed for the (often quarterly) addition and deletion of constituents as well as regular corporate events, smart beta indexes exhibit higher levels of turnover than their cap-weighted counterparts (see, for example, Amenc et al., 2011).

Importantly, for any level of liquidity, the level of turnover in the index will impact the performance of the tracking fund through the frequency of occurrence of transaction costs. Clearly, investing in smart beta indexes requires investors to have access to solutions where implementation costs and liquidity risks are thoroughly considered.

Providers and investors agree that smart beta strategies incur additional costs to trade compared to cap-weighted indexes; however, what remains unanswered is how to measure these costs reliably. Typical backtest performances of smart beta strategies offered by commercial index providers do not consider real-life transaction costs. Index providers prefer to leave it to market participants to figure out what the costs of trading those strategies would be, or they rely on some arbitrary assumptions on transaction cost levels. At the same time, there are also some market participants who make bold claims that smart beta strategies experience a significant drag in terms of implementation costs, to the extent of rejecting the value-add of all smart beta strategies. Unfortunately, such claims are not usually accompanied by actual measures of implementation costs. In the absence of actual costs, such claims cannot be evaluated.

In this article, we address this gap by introducing a suite of analytics developed by ERI Scientific Beta specifically to enable investors to assess the investability of smart beta indexes and help them make informed decisions about whether smart beta indexes add value in excess of the costs incurred to implement them. We briefly describe how the metrics are defined and their utility in assessing the investability of the indexes, along with a performance report of their application to actual indexes.

Investability metrics

ERI Scientific Beta has developed a set of analytics specifically to assess the investability of our indexes, given that there is a significant gap in that area in performance reporting in the industry. For example, there is extensive academic literature that discusses simple ways to assess the trading costs of smart beta strategies, yet index providers do not seem to apply them in assessing their actual cost estimates. Price impact is another example of a hidden cost that is often ignored. In order to address these shortcomings in performance reporting regarding the investability of smart beta indexes, ERI Scientific Beta has developed a set of analytics that provides a comprehensive analysis of the investability of its indexes. In this section, we describe these investment analytics briefly, especially their definition, economic interpretation and finally the empirical assessment of the investability of our smart factor indexes using these analytics. The investability of smart beta indexes can be assessed according to different dimensions such as liquidity, capacity, transaction costs, etc. ERI Scientific Beta’s investability analytics comprehensively cover these different dimensions. We will thoroughly assess the investability of Scientific Beta’s smart factor indexes along these various dimensions using these analytics.

The investability analytics are categorized into three groups.

1. Turnover and transaction costs
2. Liquidity indicators
3. Days-to-trade and price impact

Below, we review each of these in detail.

Turnover and transaction costs

Turnover

Turnover refers to the measurement of how frequently, and in which relative proportions, the constituents of an equity strategy index are traded over a specific period. Turnover, which leads to transaction costs that are higher than those of buy-and-hold strategies and which may make it harder to replicate the index, is of concern to index investors.

The turnover is calculated as the sum of absolute deviations of individual weights (or positions) between the end of a quarter and the beginning of the following quarter.

Transaction costs

Transaction costs play a major role in the performance drag of smart beta strategies. In a recent EDHEC-Risk Institute study (Easakia et al. (2017)), the authors compute intra-day spread estimates using low frequency data (daily data) by drawing upon recent advances in market microstructure literature and apply them to popular smart beta strategies. We draw upon that study to compute transaction costs for all of our smart factor offerings. Total trading costs can be decomposed into three components: the spread, the price impact, and commissions (see, e.g., Hasbrouck (2007)). Commissions are usually insignificant for large institutional investors and are very institution-specific. The spread reflects the cost of a round trip trade (buy and sell). The basic cost definition is the percentage quoted spread which reflects the percentage cost of buying at the ask quote and selling at the bid quote. If trades occur at prices different from the bid and offer (1:1), then the effective spread is a more useful measure because in the case of large orders the effective spread captures the price impact caused by the trade as well as the realized spread (Huang and Stoll (1996)).

Estimating effective spread requires high frequency intraday data. We need to observe trades and quotes within the trading day to come up with cost measures. However, such data is both hard to use and hard to get. It is hard to use because high-frequency data is big and messy. The increasing frequency of trading has led to a huge amount of tick-by-tick price data requiring massive computational power for analysis. Fong, Holden and Trzcinka (2014), who analyze several billion data points, argue that high-frequency equity data likely grows at a rate of more than 30% per year, which outpaces the growth of computing power. Moreover, tick data requires price and quote procedures to be matched (see Lee and Ready (1991)), and intense data cleaning, so that the quality of databases and the cleaning procedures become a prime concern. High frequency data is hard to get because it is expensive, and it covers only short time periods. It is common for researchers to analyze only periods of less than a decade, sometimes only a few years, due to data availability limitations.

Fortunately, recent research has shown that there are effective ways of estimating transaction cost variables that are only observable at high frequency based on lower frequency (daily) data. The advantage of such approaches is that results can be generated for longer periods and different markets, with relative computational ease and limited data needs. There are several low-frequency measures proposed in the literature that are efficient proxies for the effective spread. We chose the method introduced by Chung and Zhang (2014), as it is widely considered the best proxy for the intra-day effective spread (see Fong, Holden and Trzcinka (2014), Chung...
Turnover and Transaction Costs


### Exhibit 1

<table>
<thead>
<tr>
<th>Dec. 31, 2006, to Dec. 31, 2016</th>
<th>Broad Cap-Weighted</th>
<th>High Factor Intensity Diversified Multi-Strategy Indexes</th>
<th>Multi-Beta Multi-Strategy (6-Factor) EW</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mid Cap</td>
<td>Value</td>
<td>High Mom.</td>
</tr>
<tr>
<td>Annualized One-Way Turnover</td>
<td>4.11%</td>
<td>45.13%</td>
<td>37.35%</td>
</tr>
<tr>
<td>Transaction Costs</td>
<td>&lt; 0.01%</td>
<td>0.03%</td>
<td>0.02%</td>
</tr>
<tr>
<td>Relative Returns</td>
<td>-</td>
<td>2.28%</td>
<td>2.43%</td>
</tr>
<tr>
<td>Relative Returns net of Costs</td>
<td>-</td>
<td>2.25%</td>
<td>2.41%</td>
</tr>
<tr>
<td>Annualized One-Way Turnover</td>
<td>4.15%</td>
<td>46.32%</td>
<td>38.33%</td>
</tr>
<tr>
<td>Transaction Costs</td>
<td>0.01%</td>
<td>0.12%</td>
<td>0.10%</td>
</tr>
<tr>
<td>Relative Returns</td>
<td>-</td>
<td>2.84%</td>
<td>2.56%</td>
</tr>
<tr>
<td>Relative Returns net of Costs</td>
<td>-</td>
<td>2.72%</td>
<td>2.46%</td>
</tr>
<tr>
<td>Annualized One-Way Turnover</td>
<td>9.38%</td>
<td>54.82%</td>
<td>39.95%</td>
</tr>
<tr>
<td>Transaction Costs</td>
<td>0.04%</td>
<td>0.26%</td>
<td>0.19%</td>
</tr>
<tr>
<td>Relative Returns</td>
<td>-</td>
<td>5.79%</td>
<td>4.25%</td>
</tr>
<tr>
<td>Relative Returns net of Costs</td>
<td>-</td>
<td>5.53%</td>
<td>4.06%</td>
</tr>
</tbody>
</table>

Liquidity Indicators

Analytics are calculated over the period Dec. 31, 2006, to Dec. 31, 2016. All average measures are weighted averages for the corresponding indexes. All cumulative measures are weighted averages multiplied by the number of stocks in the index. The average absolute volume is the weighted average ADTV of all the stocks in the index. The ADTV of a stock is calculated as the median of the quarterly average daily dollar traded volume over the last four quarters. The traded volumes are calculated from the three most liquid listings of the stock. In calculating the relative volume, the ADTV of a stock is divided by its capitalization and then this ratio is used in calculating the weighted average of the index.

### Exhibit 2

<table>
<thead>
<tr>
<th>Dec. 31, 2006, to Dec. 31, 2016</th>
<th>Broad Cap-Weighted</th>
<th>High Factor Intensity Diversified Multi-Strategy Indexes</th>
<th>Multi-Beta Multi-Strategy (6-Factor) EW</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mid Cap</td>
<td>Value</td>
<td>High Mom.</td>
</tr>
<tr>
<td>Average Market Capitalization (M$)</td>
<td>98,126</td>
<td>8,888</td>
<td>29,385</td>
</tr>
<tr>
<td>Cumulative Market Capitalization (M$)</td>
<td>49,032,194</td>
<td>1,366,997</td>
<td>4,426,426</td>
</tr>
<tr>
<td>Average Absolute Volume (M$)</td>
<td>690</td>
<td>87</td>
<td>189</td>
</tr>
<tr>
<td>Cumulative Absolute Volume (M$)</td>
<td>345,217</td>
<td>13,398</td>
<td>28,480</td>
</tr>
<tr>
<td>Average Relative Volume</td>
<td>0.009</td>
<td>0.011</td>
<td>0.009</td>
</tr>
<tr>
<td>Cumulative Relative Volume</td>
<td>4.422</td>
<td>1.645</td>
<td>1.316</td>
</tr>
<tr>
<td>Average Market Capitalization (M$)</td>
<td>71,735</td>
<td>6,269</td>
<td>21,773</td>
</tr>
<tr>
<td>Cumulative Market Capitalization (M$)</td>
<td>140,571,683</td>
<td>12,978,101</td>
<td>14,119,157</td>
</tr>
<tr>
<td>Average Absolute Volume (M$)</td>
<td>445</td>
<td>53</td>
<td>127</td>
</tr>
<tr>
<td>Cumulative Absolute Volume (M$)</td>
<td>875,123</td>
<td>32,115</td>
<td>75,679</td>
</tr>
<tr>
<td>Average Relative Volume</td>
<td>0.007</td>
<td>0.008</td>
<td>0.007</td>
</tr>
<tr>
<td>Average Market Capitalization (M$)</td>
<td>18,718</td>
<td>1,458</td>
<td>4,284</td>
</tr>
<tr>
<td>Cumulative Market Capitalization (M$)</td>
<td>12,932,939</td>
<td>928,367</td>
<td>915,362</td>
</tr>
<tr>
<td>Average Absolute Volume (M$)</td>
<td>75</td>
<td>6</td>
<td>16</td>
</tr>
<tr>
<td>Cumulative Absolute Volume (M$)</td>
<td>51,852</td>
<td>1,314</td>
<td>3,354</td>
</tr>
<tr>
<td>Average Relative Volume</td>
<td>0.005</td>
<td>0.005</td>
<td>0.004</td>
</tr>
<tr>
<td>Cumulative Relative Volume</td>
<td>3.537</td>
<td>0.962</td>
<td>0.885</td>
</tr>
</tbody>
</table>
Days-to-Trade and Price Impact

Analytics are calculated over the period Dec. 31, 2006, to Dec. 31, 2016. In calculating Days to Trade (DTT) of an index (both effective and maximum DTT), we assume an investment of USD 3 billion in a global cap-weighted index in June 2016. The effective DTT is reported as the quarterly average of index DTT for the past 10 years/40 quarters, whereas maximum DTT is reported only for the latest quarter. In both cases, every quarter, first we calculate the DTT of a stock assuming daily trading volume used up is 10% and then the DTT of a portfolio is calculated as the 95th percentile value. In the case of effective DTT, we only consider changes in the weight of a stock, whereas in the case of maximum DTT, we use the weight of a stock instead of the change in weight at rebalancing. The Amihud illiquidity ratio of an index is the weighted average Amihud measure of stocks, which in turn is calculated as the ratio of absolute daily returns in local currency to the daily dollar traded volume. Source: www.scientificbeta.com.

<table>
<thead>
<tr>
<th>Dec. 31, 2006, to Dec. 31, 2016</th>
<th>Broad Cap-Weighted</th>
<th>High Factor Intensity Diversified Multi-Strategy Indexes</th>
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</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mid Cap</td>
<td>Value</td>
<td>High Mom.</td>
</tr>
<tr>
<td>Maximum Days-to-Trade (as of last rebalancing date)</td>
<td>0.23</td>
<td>2.29</td>
<td>2.32</td>
</tr>
<tr>
<td>Effective Days-to-Trade</td>
<td>0.01</td>
<td>0.39</td>
<td>0.21</td>
</tr>
<tr>
<td>Amihud Illiquidity Ratio</td>
<td>0.11</td>
<td>0.21</td>
<td>0.13</td>
</tr>
<tr>
<td>Maximum Days-to-Trade (as of last rebalancing date)</td>
<td>0.38</td>
<td>6.76</td>
<td>5.18</td>
</tr>
<tr>
<td>Effective Days-to-Trade</td>
<td>0.04</td>
<td>1.54</td>
<td>0.77</td>
</tr>
<tr>
<td>Amihud Illiquidity Ratio</td>
<td>0.72</td>
<td>2.23</td>
<td>1.47</td>
</tr>
<tr>
<td>Maximum Days-to-Trade (as of last rebalancing date)</td>
<td>0.88</td>
<td>10.52</td>
<td>7.75</td>
</tr>
<tr>
<td>Effective Days-to-Trade</td>
<td>0.09</td>
<td>2.28</td>
<td>1.07</td>
</tr>
</tbody>
</table>

Importantly, for any level of liquidity, the level of turnover in the index will impact the performance of the tracking fund through the frequency of occurrence of transaction costs.
Smart beta strategies do incur additional costs compared to cap-weighted indexes. A reasonable expectation from an investor’s perspective is that providers should disclose the level of costs generated by their strategies in order to provide information on net returns. However, providers typically fail to make explicit adjustments for implementation costs and merely report gross returns, leaving it to other market participants to figure out what the costs are like. Scientific Beta addresses this gap by introducing a suite of analytics developed specifically to enable investors to assess the investability of smart beta indexes. These analytics show that while it is true that smart beta strategies incur additional costs, carefully designed indexes with a focus on investability do generate relative returns in excess of the costs. It is worth emphasizing that none of these analytics relies on any proprietary data. They are computed using readily available low-frequency market data with no major computational overhead and a transparent methodology that can be easily replicated, and so there is no reason why smart beta index providers should delegate the investability assessment to the market participants, especially when it is one of the key elements in smart beta investment decision making. In order to improve transparency and enable investors to better assess the smart beta strategies, these metrics should be widely used in the industry.

CONCLUSION

A reasonable expectation from an investor’s perspective is that providers should disclose the level of costs generated by their strategies in order to provide information on net returns.
Multi-factor index providers debate the respective merits of the "top-down" and "bottom-up" approaches to multi-factor equity portfolio construction. Top-down approaches assemble multi-factor portfolios by combining distinct sleeves for each factor. Bottom-up methods build multi-factor portfolios in a single pass by choosing and/or weighting securities by a composite measure of multi-factor exposures.

The top-down approach is simple and transparent and investors can control allocations across factors easily. Being typically assembled from reasonably diversified factor sleeves, top-down multi-factor portfolios avoid being concentrated in a few stocks. Bottom-up portfolios have been used to concentrate portfolios in "factor champions," where one emphasizes stocks that score highly on average across multiple factors. This allows interactions across factors to be taken into account and avoids diluting exposures (such as diluting exposure to value when tilting to high profitability).

It has been argued that bottom-up approaches produce additional performance. However, studies of bottom-up approaches that document increased returns are typically based on selected combinations of factors (Bender and Wang (2016)) and short samples (FTSE (2016)). They also do not test for significance or robustness, and do not scrutinize risks.

Approaches that document increased returns are typically based on selected combinations of factors and short samples. Moreover, in a recent study, Amenc et al (2017) have shown that accounting for the cross-sectional interaction of exposure to multiple factors. This allows interactions across factors to be taken into account and avoids diluting exposures (such as diluting exposure to value when tilting to high profitability).

Recent studies have argued that bottom-up approaches produce additional performance. However, studies of bottom-up approaches that document increased returns are typically based on selected combinations of factors and short samples. Moreover, in a recent study, Amenc et al (2017) have shown that accounting for the cross-sectional interaction of exposure to multiple factors. This allows interactions across factors to be taken into account and avoids diluting exposures (such as diluting exposure to value when tilting to high profitability).

Against this backdrop, we contrast the claims of the proponents of bottom-up approaches with relevant findings in the academic literature. In the first section, we review general insights from the literature on return estimation and factor models that are relevant for multi-factor portfolio construction. In the second section, we discuss recent literature that specifically addresses issues with bottom-up portfolio approaches.

Does it make sense to account for fine-grain differences in factor exposures?

A key idea behind bottom-up approaches is precisely to account for stock-level differences in terms of exposure to multiple factors. While it is understandable that computational technicians will have a tendency to try to account for factor exposures with the highest possible precision, it is worth considering insights from finance. There are two findings in empirical asset pricing that question the relevance of the type of over-engineering present in bottom-up approaches.

Stock-level estimates are noisy

Empirical evidence on factor premia overwhelmingly suggests that the relationships between factor exposures and expected returns do not hold with a high level of precision at the individual stock level. Indeed, factor scores are used as proxies for expected returns, which are notoriously difficult to estimate and inherently noisy at the stock level (see Merton (1980) and Black (1993a)).

Rather than trying to determine differences in returns between individual stocks, researchers have created groups of stocks and tested broad differences in returns across these. This “portfolio method” ensures robustness by ignoring stock-level differences and refraining from modeling multi-variate interactions. For this reason, studies that document factor premia (such as Fama and French (1993)) rely on portfolio-sorting approaches. In particular, Black (1993b, p. 77) emphasizes: “I am especially fond of the ‘portfolio method.’ Nothing I have seen … leads me to believe that we can gain much by varying this method.”

There is ample evidence suggesting that factor characteristics do not provide an exact link with individual stock returns (see Caderburg and O’Doherty (2015)) and often this is not even monotonous (see Patton and Timmermann (2010)). Thus, fine-grain differences in factor exposures may not translate into return differences.

To illustrate the lack of precision in the relationship between factor exposure and returns, we provide results for fine-grain portfolio sorts. In particular, we first sort quintile portfolios by factor characteristics (such as book-to-market for "value"), and then in a second sort each quintile is again subdivided into sub-quintiles according to the same factor score. If the relationship between factor exposure and returns was highly precise, the second sort for stocks with broadly similar characteristics should lead to meaningful return differences.

To be more specific, even when looking at stocks in the same book-to-market quintile, the distinction by sub-quintile in a second sort should lead to a positive value premium being observed for those stocks that are more value-oriented (higher book-to-market ratio) within their respective quintile. However, as can be seen from Exhibit 1, the sub-quintile premia are negative in most cases. Especially in the lower quintile (Q5), distinguishing between stocks based on factor scores does not add any value. In fact, for four out of the six factors we analyzed, selecting the highest-exposure stocks among the top quintile stocks leads to lower returns than selecting the stocks with the relatively lowest exposure in the top quintile. In other words, among stocks with high exposure to a given factor (top quintile stocks), making a finer distinction between those that are most strongly exposed and those that are relatively less strongly exposed does not lead to higher returns. This clearly shows that even though the risk premium appears in broadly diversified portfolios, it disappears if we start accounting for differences at the stock level or create very narrow portfolios according to precise differences in exposures.
Single factor relationships may break down at the multi-factor level. While there is ample evidence that portfolios sorted on a single characteristic are related to robust patterns in expected returns, such patterns may break down when incorporating many different exposures at the same time. For example, Asness (1997, p. 29 and p. 34) observes: “Value works well on average, but largely fails for firms with high momentum. Momentum works, in general, but is particularly strong for expensive firms.” As a result, “increasing both Momentum and Value simultaneously has a significantly weaker effect on stock returns than the average of the marginal effects of increasing them separately.” This weakening would impact securities favored by composite scoring methods.

A more drastic failure is discussed by Stambaugh, Yu and Yuan (2015). The authors show that, even though the low volatility anomaly exists in the broad cross section of stocks, low volatility stocks actually underperform when considering only stocks that rank well on a composite multi-factor score.

Could the backtest performance of bottom-up approaches be over-stated? A backtest is a simulation of a portfolio performance as if it were implemented historically. It is not rare to find strategies that provide stellar performance in backtests but fail to deliver robust live performance. There are several reasons for such a lack of robustness. Firstly, backtests are sensitive to the sample period of the tests. This problem arises simply because returns are highly sample-specific. Secondly, the results of backtests are often contaminated by data mining and over-fitting. Lo and MacKinlay (1990) wrote that “the more scrutiny a collection of data is subjected to, the more likely will interesting (spurious) patterns emerge.” If one generates and tests enough strategies, one will eventually find a strategy that works very well in backtest. Over-fitting occurs when more and more degrees of freedom are added to the model until the model might actually be capturing sample-specific noise rather than structural information. Over-fitted models tend to fail miserably out-of-sample.

The bottom-up approach to multi-factor investing has opened up a platform for computational technicians to come up with several possibilities for selecting and weighting factor metrics in multi-variate composite scores. Such post hoc combinations exacerbate data-mining problems by introducing over-fitting and selection biases (see Novy-Marx (2016)). Knowing that the bottom-up approaches are by design prone to selection bias, an important question worth exploring is whether the claims of bottom-up proponents could be due to statistical flukes. A simple way to do that is by adjusting the results for the inherent biases. The discussion below explores this question in detail by summarizing results from a recent study (Leippold and Ruegg (2017)).

Even though the multiple testing bias has been extensively analyzed in the literature (see McLean and Pontiff (2016), Harvey, Liu, and Zhu (2016) and Bailey and Lopez de Prado (2018)), studies claiming that bottom-up approaches provide better risk-adjusted returns than top-down approaches do not account for this issue (see Bender and Wang (2016)). Moreover, tests are done on short time periods such as 15 years (see FTSE (2016)) while a reasonable empirical assessment of factor investing approaches substantiably longer time period (40 years or more) to account for the cyclical nature of risk factors.

A recent study (see Leippold and Ruegg (2017)) re-assesses claims that a bottom-up approach to multi-factor portfolio construction leads to superior results. When applying proper statistical robustness checks, and adjusting for relative risk, they find that there is no such superiority.

Leippold and Ruegg account for the fact that there are numerous variations one could employ to conduct such tests and any reported superior performance of the bottom-up approach would be the result of picking a favorable combination that happens to “work” simply due to chance. The authors test a large variety of factor combinations and portfolio construction methods, and compare the bottom-up and top-down approach in each case. They use advanced statistical tools to adjust for the fact that apparently significant benefits will easily result as a fluke if the number of combinations is large enough.

This analysis shows that there is no evidence that bottom-up approaches perform better than the corresponding top-down approaches. Thus, the findings reported by promoters of bottom-up approaches do not withstand rigorous analysis and could instead be explained by the choice of a particular selection of factors, and failure to adjust for the data-mining possibilities offered for such analysis. The table below presents a summary of the results. The authors create 78 different multi-factor portfolios using all possible combinations of up to five popular factors (value, momentum, investment, profitability and low volatility) and three different portfolio construction methods. Only 13% of the possible variations lead bottom-up portfolios to have significantly higher Sharpe ratios than their top-down counterpart. This finding invalidates the claims of superiority made by proponents of bottom-up approaches.

While, some claim that bottom-up portfolios generate superior performance, a thorough analysis shows that the evidence does not support such claims. For investors, it is important to keep in mind the potential data-mining pitfalls associated with backtests. Leippold and Ruegg (2017, p. 24) note: “Given the increasing computational power for conducting multiple backtests and given the fact that financial institutions have incentives to deliver extraordinary results, it is crucial to apply the most advanced statistical testing frameworks, ignoring the available tools can lead to hasty conclusions and misallocation of capital to investment strategies that are false discoveries.”

While providers are entitled to rely on short-term backtests to conclude on the superiority of their approach, investors would be well advised to consider the findings in the academic finance literature and to use advanced statistical tools when they evaluate the benefits of bottom-up approaches.

References


A SUPPLEMENT TO PENSIONS & INVESTMENTS Research for Institutional Money Management
Factor investing is an investment paradigm under which an investor decides how much to allocate to various factors, as opposed to various securities or asset classes. Its popularity has been growing since the turn of the millennium, especially after the recognition in 2008 that multiple asset classes can experience severe losses at the same time despite their apparent differences. The term “factor,” however, is used with many different meanings depending on the context and the targeted application. The main goal of this article is to provide clarification with respect to the various possible definitions of factors that are relevant in investment practice. This article also develops a framework for allocating to factors in two main contexts, namely allocation decisions at the asset class level, and benchmarking decisions within a given class. For each of these applications, we examine the three most important questions raised by the adoption of a factor investing approach: (i) why think in terms of factors? (ii) what factors should be chosen? and (iii) how do we allocate between them?

Several definitions for factors co-exist, which differ in terms of asset vs. the time-series properties of assets.

The various notions of factors are not mutually exclusive and can be combined within a comprehensive framework for factor allocation.

It is possible to use factor indexes as building blocks and to diversify risk across underlying factors, or to seek to exploit knowledge of economic regimes to design portfolios that react to changes in market conditions.

Maximizing the Benefits of Factor Investing

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Diversification with risk factors.


Note 2: By construction, the factor risk parity portfolio is not unique, so we select the one with the lowest leverage (sum of absolute values of short positions) in Panel (b).

(a) Effective number of uncorrelated bets for selected portfolios.

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>PCA factors</th>
<th>MLT factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Policy portfolio</td>
<td>1.34</td>
<td>3.40</td>
</tr>
<tr>
<td>Equally-weighted</td>
<td>1.08</td>
<td>3.77</td>
</tr>
<tr>
<td>Risk parity</td>
<td>2.00</td>
<td>6.00</td>
</tr>
<tr>
<td>Minimum variance</td>
<td>2.67</td>
<td>2.28</td>
</tr>
</tbody>
</table>

(b) Composition of risk parity and factor risk parity portfolios (in %).

<table>
<thead>
<tr>
<th>US Equities</th>
<th>Int’l Equities</th>
<th>US Treasuries</th>
<th>US Corporate</th>
<th>US Tips</th>
<th>Commodities</th>
<th>Real Estate</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Risk parity</td>
<td>7.4</td>
<td>6.3</td>
<td>40.6</td>
<td>16.4</td>
<td>18.5</td>
<td>6.2</td>
<td>4.6</td>
</tr>
<tr>
<td>Risk parity - PCA</td>
<td>13.7</td>
<td>-11.7</td>
<td>98.9</td>
<td>-33.3</td>
<td>12.0</td>
<td>15.7</td>
<td>4.7</td>
</tr>
<tr>
<td>Risk parity - MLT</td>
<td>15.0</td>
<td>4.3</td>
<td>42.1</td>
<td>18.2</td>
<td>15.5</td>
<td>5.3</td>
<td>-0.4</td>
</tr>
</tbody>
</table>
named principal component analysis and minimum linear torsion (see Carl, Deguest and Martellini (2014) for a review, and the example of implementation below).

Finally, a third possible definition for a factor in practice is as a state variable that contributes to explaining time variation in the risk premia, volatilities and correlations of assets. This definition takes a time-series perspective, unlike the previous one, which aim to explain cross-sectional properties. The risk and return characteristics of assets can be compared across regimes defined in terms of macroeconomic variables that have an impact on discount rates or expected future cash flows. It is also standard practice to take state variables as the dividend yield as a predictor of stock returns, or use the forward-spot spread to predict bond returns. It should be noted that financial theory establishes connections between the three practical categories of factors and the explanation of the pricing factor: the risk-based measure for profitability of passive strategies is that they are exposed to rewarded pricing factors, the Arbitrage Pricing Theory of Ross shows that common risk factors can be pricing factors, and the International Capital Asset Pricing Model of Merton implies that state variables that predict changes in investment opportunities are pricing factors.

At the asset class level, risk factors allow the diversification of a portfolio to be assessed in a more meaningful way than dollar weights, and they are involved in the construction of liability-hedging portfolios by factor matching techniques. Conditioning factors are useful to design performance-seeking portfolios that react to market conditions.

Modern portfolio theory gives a clear definition of what a “well-diversified” portfolio should be: it should have the highest Sharpe ratio, equal to the reward, measured as expected excess return over the risk-free rate, per unit of risk, measured as volatility. This prescription is hard to implement in practice, due to the strong uncertainty over expected return estimates, which research has shown to have a dramatic impact on performance. To alleviate the concern over parameter uncertainty, one may decide to go back to conventional wisdom and diversity by spreading eggs across baskets, which hopefully leads to more efficient collection of risk premia across assets. A standard interpretation of this principle is to weight constituents equally, but it opens the door to portfolios with concentrated risk: the risk of a 50%-50% stock-bond portfolio is mostly explained by stocks. Factor contributions are easiest to calculate when the factors are uncorrelated from each other because there are then no cross-correlation terms to divide between factors. As introduced earlier, uncorrelated risk factors that completely explain uncertainty in a given universe can be obtained by (at least) two statistical procedures, namely principal component analysis (PCA) and minimum linear torsion (MLT). The latter method was introduced more recently, and it aims to address some of the shortcomings of PCA by minimizing the distortion of factors with respect to the original assets: this property facilitates the economic interpretation of factors and enhances robustness across samples.

Exhibit 1 shows an example of the ENUB calculation in a seven-asset class universe (equities, bonds, commodities and real estate). The four benchmark portfolios have ENUBs much lower than the theoretical maximum of seven, which means that their risk is concentrated in a few risk factors, except for the risk parity allocation when MLT factors are employed; indeed, each MLT factor is close to an asset, so the risk parity portfolio should not be exceedingly far from a factor risk parity portfolio. Nevertheless, the true factor risk parity portfolio for MLT factors has a different composition than the risk parity one. With PCA factors, it is virtually impossible to achieve factor risk parity with a long-only allocation, since the first factor will inevitably dominate the others, so sizeable short positions must be used. This example illustrates the fact that MLT factors are computationally easier to handle.

Risk factors are also naturally involved in a different context, where the objective is not to efficiently diversify across assets, but to replicate a benchmark as closely as possible, like in asset-liability management, where a good liability-hedging portfolio (LHP) is needed. Through the discounting mechanism of future cash flows, interest rate risk is a major source of risk, and often the dominant one, in liabilities, so aligning the interest rate exposures of assets and liabilities is the first step toward the construction of a LHP. The difficulty here is that exposures are not linear, so linear approximations are needed. The first-order approximation leads to duration matching, which is effective at immunizing the funding ratio against small changes in the yield curve, but in order to hedge against risks of larger changes, finer approximations are required, involving a matching of convexities in addition to duration alignment.

Beyond risk factors, state variables characterizing time-varying investment opportunities may prove useful in asset allocation, in order to construct a performance-seeking portfolio (PSP) that adapts to market conditions. A simple way to define regimes is to look at inflation and growth in gross domestic product and to make a distinction between four regimes, depending on whether inflation and growth are below or above their mean values. The results in Exhibit 2 show that equities do best when inflation is modest and growth is dynamic, while the low growth and high inflation regime is the least favorable to them, both in terms of performance and volatility. Commodities perform better in the high inflation than in the low inflation periods, and Treasuries deliver their best performance in the low growth and high inflation regime, thereby confirming their role of a “safe haven.” These results suggest that regimes of growth and inflation can be used to adapt the relative weighting of asset classes as a function of market conditions.

By equating the contributions of assets to risk, the risk parity approach to allocation is a big step toward addressing this issue, but it still misses the fact that constituents are exposed to common sources of risk. To assess the level of diversification of a portfolio in terms of risk factors, we propose to calculate the effective number of uncorrelated bets (ENUB), a quantitative measure of the deconcentration of factor contributions to portfolio volatility that is minimal when risk is concentrated in a single factor, and maximal when all factors contribute equally to risk. The latter condition defines a factor risk parity portfolio.

Within an asset class, theory makes a case for factor investing by showing that the maximum Sharpe ratio (MSR) portfolio of individual securities coincides with the MSR portfolio of pricing factors, no matter how large the universal universe is. Empirically, equity factor indexes representing the six well-documented factors (size, value, momentum, volatility, profitability and investment) explain the vast majority of the capital weighted index in terms of risk-adjusted return, especially if they are “smart weighted.” Further improvement over the risk-return characteristics of individual factors is achieved by building multi-factor portfolios.

Going back to the theoretical definition of a well-diversified portfolio as the maximum Sharpe ratio (MSR) portfolio, a theoretical result that we prove in this paper is that the MSR portfolio of any set of assets coincides with the MSR portfolio of factors, provided the latter are pricing factors in the sense of asset pricing theory. This result holds regardless of the number of assets, so it represents a substantial reduction in dimensionality if there are many of them, as is generally the case in bond markets. It also provides the usual form of the “two-step process,” in which an allocation exercise to multiple securities is divided into two steps, namely the grouping of securities in benchmarks, and then an allocation to the benchmarks.

This theoretical result cannot be directly applied in practice to calculate the MSR portfolio because a complete set of pricing factors is not known, but the idea of dimension reduction can be exploited with other types of factors, namely risk factors. Indeed, under a factor model, each return can be decomposed into a systematic part that is a sum of factor exposures, plus an idiosyncratic term, and provided idiosyncratic returns are uncorrelated across assets, the number of independent parameters to estimate in the covariance matrix is much smaller than if no factor structure is postulated. Considering, for instance, a universe of N = 500 stocks, it is shown in the paper that the number of covariances is 125,250 without a factor model, 3,521 with six factors and 2,006 with three of them. In other words, the use of risk factors alleviates the curse of dimensionality for the estimation of the covariance matrix. This idea is implemented in BARRA models, as explained in the Barra Risk Model Handbook.

Though a comprehensive set of pricing factors has not been uncovered to date, it is well known from a large body of empirical research that at least in the equity class, factors understood as profitable strategies provide a substantial improvement over the standard cap-weighted index in terms of risk-return characteristics. Exhibit 3 summarizes this evidence by assuming factors to be a set of long-only factor indexes made of stocks with a given characteristic: mid-market capitalization, high book-to-market, high past one-year return, low volatility, high gross profit-to-asset ratio or low total asset growth. The base case version of these indexes is cap-weighted, but “smart factor indexes” deviate from this weighting scheme in order to better diversify away unrewarded risk. Among the many possible schemes, the table considers equal weighting and inverse volatility weighting. Over the long period considered, all factor indexes perform the broad cap-weighted index and display a higher Sharpe ratio, and the smart versions bring further improvement on these figures.

The equivalence result between the MSR portfolio of securities and the MSR portfolio of pricing factors suggests that it is interesting to combine factors. Thus, the next exercise...
that we conduct consists of the construction of multi-factor equity portfolios. Exhibit 4 shows statistics for selected allocations. Given that the six factors are long only, they are all exposed to the market equity factor and they have high correlations, greater than 90%, so one may wonder what benefits can be expected from mixing such highly correlated constituents. This turns out that the annualized long-term return and the Sharpe ratio are only marginally improved with respect to the average properties of the constituents, but the relative analytics, which measure risk and return with respect to the broad cap-weighted index, are much more favorably impacted. This can be attributed to the fact that the relative correlations — that is, the correlations between excess returns — are much lower than the absolute correlations and are often negative, so diversification can be expected to be more effective from a relative perspective. In particular, the equally-weighted portfolio has much lower tracking error and a maximum relative drawdown, as well as a much higher information ratio than the average of the constituents.

The choice of the allocation method has important effects on the properties of the multi-factor portfolios.

The global minimum variance portfolio achieves its objective even on an out-of-sample basis, but does so at the cost of sizeable relative risk, while the equally-weighted portfolio displays a higher volatility, but better relative analytics. We also calculate two portfolios that maximize diversification in terms of risk factors (subject to a long-only constraint). At this stage, two notions of factors are involved — on the one hand, constituents are profitable passive equity strategies, and on the other, the weighting scheme seeks to maximize diversification in terms of underlying risk factors. The latter factors are extracted successively from the covariance matrix of the constituents and from their relative covariance matrix, which collects the covariances of excess returns. Each system of factors gives rise to its own value for the ENUB, and the two ENUBs respectively measure the deconcentration of the volatility and the tracking error. The maximum relative ENUB portfolio has lower relative risk, measured either through the tracking error or the relative drawdown, than its absolute counterpart. Additional backtests — the results of which are not reported here but can be found in the complete version of this article — show that this finding is robust to the choice of the sample period.

As a conclusion, the various notions of factors are not mutually exclusive and can be combined within a comprehensive framework for factor allocation. Further research is needed to improve our understanding of their interactions, especially in the fixed-income class.

As we argue in the previous empirical illustration, a factor allocation exercise can involve more than one notion of factors. It is possible to use factor indexes as building blocks and to diversify risk across underlying factors, or to seek to exploit knowledge of economic regimes to design portfolios that react to changes in market conditions. After five decades of research on equities, robust sources of profitability are now well identified in this class, but not as well in other classes, especially in fixed-income. Moreover, while past research has mostly focused on finding predictors for the equity market or the bond market as a whole, and while it is recognized that factor indexes have cyclicality behavior, further investigation is needed to quantify the degree of predictability in these factors and to identify relevant predictors.

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References

• Martellini, L. and Milhau, V. 2018 Smart Beta and Beyond. Maximising the Benefits of Factor Investing. EDHEC-Risk Institute Publication.
The need for new retirement investment solutions

Financing consumption in retirement has arguably be- come the greatest challenge for most individuals following a number of important changes, including the weakening state pension systems and the shift from defined-benefit to defined-contribution schemes in the corporate world that has left individuals more exposed to retirement risks. With the need to supplement retirement savings via voluntary contri- butions, individuals are increasingly responsible for their own savings and investment decisions. This global trend poses substantial challenges as individual investors not only suffer from behavioral limitations, but also typically lack the expert- ise needed to make educated investment decisions.

In response to these concerns, insurance companies, in- vestment banks and asset management firms have proposed a number of so-called retirement products. There are reasons to believe, however, that these products fall short of providing satisfactory solutions to the problems faced by individuals when approaching investment saving decisions. In this paper, we describe how goal-based investing principles can be used to design scalable mass-customized forms of retirement solu- tions that can address the specific retirement needs and constraints of a large number of individuals in a parsimonious manner. As an example of the framework in application, we propose a goal-based investing strategy for retirement needs in accu- mulation that can be regarded as a simple and prag- matic risk-managed improvement over existing forms of tar- get-date funds, making them better suited to investors who are saving for retirement in the accumulation phase of their life cycle. In parallel, and in an effort to help increase aware- ness around the need for improved retirement solutions, EDHEC-Risk Institute and the Princeton Operations Research and Financial Engineering (ORFE) Department have teamed up to launch the EDHEC-Princeton Goal Based Investing Indexes. These indexes are based on joint academic re- search conducted with the support of Merrill Lynch Wealth Management on the application of goal-based investing (GBI) principles to the retirement problem.

A careful analysis of retirement investment solutions is rather timely — on June 29, 2017, the European Commission published a legislative proposal for a regulation on a pan-Eu- ropean personal pension product (PEPP). According to the proposal, PEPP providers shall offer up to five investment op- tions to PEPP savers, including a default investment option. In its current format, the Commission’s text (article 37.2) sug- gests that the default option could be accompanied by a guarantee. While it seems intuitively desirable that the default option should aim to preserve capital over time, one key con- cern is that the introduction of minimum return or capital guarantees would have a number of negative consequences.

The most important of these consequences would be an ex- ceedingly large opportunity cost for beneficiaries, given the presence of strict prudential regulations such as Solvency II, which make such guarantees prohibitively expensive. In addition to the direct opportunity cost deriving from the introduction of a formal insurance guarantee, as well as the costs implied by the typical distribution channels for such guaranteed products, one may also be concerned by the in- direct opportunity costs implied by the use of low-yielding fixed-income instruments in the hedging component of the guaranteed products. Moreover, the typical use of single-class liquid underlying instruments such as stock indexes for guar- anteed products (as opposed to well-diversified multi-asset portfolios) may also contribute to a lack of diversification. In this context, the enhanced upside potential offered by life-cycle strategies, also known as target-date fund strate- gies, may seemingly make them attractive alternatives due to the fact that these are inherently designed as low-risk strat- egies that explicitly benefit from the well-documented presence of mean-reversion in risk premia to be found in the equity market and beyond.

On the other hand, target-date funds offer a sole focus on an investment horizon without any protection of investors’ min- imum retirement needs. In particular, these products are not engineered to deliver replacement income in retirement, and do not adequately hedge the main risks related to retirement investment decisions, namely investment risk, interest rate risk, inflation risk and longevity risk. Another important restriction is that most target-date funds do not allow for revisions of the asset allocation as a function of changes in market conditions. This is entirely inconsistent with academic prescriptions and also, perhaps more importantly, with common sense, which both suggest that a meaningful investment strategy should also display an element of dependence on the state of the economy as well as a dependence on investors’ goals.

Replacement income, not absolute wealth, should be the focus.

Currently available investment options hardly provide a satisfying answer to the retirement investment challenge and most individuals are left with an unsatisfying choice. On the one hand, they have safe strategies with very limited upside potential, which will not allow them to generate the kind of target replacement income they need in retirement; on the other, they have risky strategies offering no security with re- spect to minimum levels of replacement income.

The most natural way to frame an investor’s retirement goal is in terms of how much lifetime guaranteed replacement income they will be able to afford at retirement. More often than not, investors in accumulation are concerned with the purchasing power of their replacement income in terms of consumption goods and services in retirement. Given that the biggest risk in retirement is the risk of outliving one’s re- tirement assets, securing replacement income within the de- cumulation period can be achieved with annuities (possibly inflation-linked or cost-of-living-adjusted), which are the true risk-free assets for individuals preparing for retirement. Annu- i ty products, however, are cost inefficient, irreversible, and do not contribute to bequest objectives. These ele- ments undoubtedly explain the low demand for annuities, a.k.a. the “annuity puzzle,” when annuitization is not incenti- tized or mandatory. A good case can actually be made that annuitization is a decision that is best taken close to re- tirement, if ever.

In the United Kingdom, the 2015 Pension Act, which has nullified the compulsory annuity purchase, creates a tremen- dous opportunity for asset managers to launch meaningful forms of retirement solutions. A key ingredient in these retire- ment solutions is a novel form of retirement bond portfolio, where the key focus should be on generating replacement in- come for a period roughly corresponding to the average life expectancy in retirement (say, for 15 or 20 years after the re- tirement date). In parallel, late-life annuities can be purchased in decu- mulation to obtain protection against tail longevity risk. It would actually be extremely useful for governments and cen- tral banks to start issuing these “retirement bonds.” While most existing bonds are useful for corporations and sovereign states to finance their activities, they are not useful investment vehicles for investors. Indeed, investors in the accumulation phase of their life cycle do not need a stream of coupon pay- ments plus principal at maturity date, which is the typical structure of available bond offerings. What individuals need are bonds paying no cash flow in the accumulation phase — that is, no cash flows until the retirement date, and then pay- ing monthly, quarterly or annual (possibly inflation-linked) coupons for a given number of years (e.g., 15 or 20 years in retirement) and no principal at the maturity date.

In the absence of such retirement bonds, forward-start bond ladder structures can be synthesized via standard cash- flow-matching or duration-matching techniques to obtain a dedicated retirement goal-hedging portfolio (GHP). Purchasing $1 worth of face value of the synthetic retirement bond is thus equivalent to securing an additional $1 worth of replace- ment income (possibly inflation-linked) say for the first 15 or 20 years in retirement.

To illustrate the fact that assets such as a Treasury bond portfolio or a money market account (which are traditionally regarded as safe investments) are actually highly risky when it comes to securing a stream of replacement income cash-
flows. Exhibit 1 plots the monthly returns on these investments in absolute terms and relative to the present value of replacement income. Returns on money market accounts (cash) are very stable and consistently close to zero, while Treasury bond returns exhibit more short-term volatility. Note that they both appear much less volatile than the returns on the GHP, which is more exposed to interest rate risk because of its long duration. Note, however, the picture is completely different when returns are computed with respect to the retirement bond price (i.e., relative to purchasing owner in terms of replacement income). By construction, the GHP does indeed have zero relative risk, while cash and bonds now appear to be highly risky. Overall, the distinction between absolute and relative risk, which is well established in asset-liability management, is also of key relevance in the retirement funding problem — replacement income, not absolute wealth, should be the focus!

Given the price of the retirement bond (that is, given the market value of replacement income cash flows), it is straightforward to calculate the purchasing power of a given level of retirement savings in terms of replacement income, (that is, the level of replacement income that these savings can finance). It is equal to the value of savings divided by the retirement bond price. As such, the retirement bond price, which provides the proper reference point, or numeraire, is an important piece of information in goal-based reporting. In what follows, we argue from a risk management standpoint that it is also useful for the construction of strategies that maximize the probability of reaching target levels of replacement income.

Key requirements for improved goal-based retirement solutions

Individuals can set target levels of replacement income expected from retirement savings as a function of their estimated consumption needs in retirement as well as income generated by other sources such as Social Security and employer-sponsored pension plans. Should a replacement income target be affordable given the current level of retirement, it could be secured by investing the required amount of wealth in the GHP.

In most cases, however, individuals and households are under-funded; their replacement income needs in retirement exceed what can be financed via savings alone. In other words, the desired replacement income level is not affordable and therefore represents an aspirational goal (in the terminology of Chhabra et al. (2015)), the presence of which justifies the need for upside performance. In this context, a well-designed retirement solution should simultaneously generate a high probability for individuals to achieve their aspirational/target levels of replacement income, but it should also secure some essential/minimum levels of replacement income in order to ensure that basic needs in retirement will be satisfied regardless of market performance.

The recognition that investors aspire to secure both essential and aspirational goals with high probabilities is leading to the new GBI investment paradigm in individual money management, where investors’ problems can be fully characterized in terms of their goals. Goal-based investing is the counterpart of liability-driven investing (LDI), which has become the relevant paradigm in institutional money management where investors’ problems are broadly summarized in terms of their liabilities.
From a financial engineering standpoint, any GBI retirement solutions should be grounded on sound and robust risk-management principles and involve the following ingredients:

- A dedicated safe GHP that replicates risk factor exposures in investors’ replacement income goals (dynamic replicating bond portfolio for the aforementioned retirement bonds);
- A common well-rewarded risky PSP that efficiently harvests risk premia in equity markets;
- A dynamic allocation to the PSP vs. GHP portfolios that secures minimum replacement income levels while generating a high probability of achieving target replacement income levels.

As such, the framework builds upon a comprehensive and holistic integration of the three forms of risk management — namely, hedging, diversification and insurance — in contrast with existing products or approaches used in institutional or individual money management, which are only based on selected risk management principles. While each of these sources of added value is already used to some extent in different contexts, a comprehensive integration of all these elements within a comprehensive disciplined investment management framework is required for the design of useful investment solutions. In the next section, we provide an example of implementation of goal-based investing principles applied to retirement, and present design features that have been used in the EDHEC-Princeton Goal Based Investing Index series.

Introducing a new generation of risk-managed target-date retirement solutions

Let us consider for concreteness an investor preparing for retirement who seeks to obtain protection on a yearly basis with respect to the purchasing power in terms of replacement income in decumulation of any contribution made in accumulation or transition phases. Assuming for simplicity that contributions are made once a year, say, at the end of December, one would naturally introduce the essential goal to cap the loss relative to replacement income to a fixed limit, e.g., 20%, over a calendar year. This short-term essential goal commands a floor that the strategy should respect at all times, and is equal to 20% of the price of the retirement bond that pays the replacement income that was affordable at the beginning of the year. This floor is reset every year to be equal to 80% of current savings, including the annual contribution.

Protection of the floor can be achieved by the means of a dynamic insurance strategy, in which the dollar allocation to the PSP is taken to be a multiple of the risk budget or margin for error, defined as the distance between current wealth and floor levels. Thus, if \( w_{PSP,t} \) denotes the percentage allocation to the PSP and \( m_t \) is the (time-varying) multiplier, we obtain an allocation that reacts to changes in the risk budget according to the following linear rule, with a rebalancing frequency taken to be monthly in our base case analysis:

\[
\begin{align*}
\frac{w_{PSP,t+1}}{w_{PSP,t}} &= m_t \left[ 1 - \frac{F_t}{W_t} \right].
\end{align*}
\]

For more detail, see Giron et al. (2018). The allocation to the PSP is typically capped to 100% to avoid leverage.
In order to anchor the design of the retirement GBI solutions with respect to existing target-date fund, we set the value of the multiplier at the beginning of every year in such a way that the percentage allocation to the PSP, taken for simplicity to be some equity index, matches the equity allocation of a deterministic target-date fund. This allows us to benefit from mean-reversion in equity markets, which implies that the allocation to equities should be higher for younger investors. With this rule, the multiplier is the deterministic function plotted in Exhibit 3, and the GBI strategy has exactly the same allocation to its performance-seeking equity component as the corresponding target-date fund at the beginning of each year. Within any given year, however, the allocation to equities does not stay constant and instead reacts to changes in the distance between current wealth and the floor, to protect the essential goal. 8

To compare the risk-managed target-date retirement strategy to its standard target-date fund benchmark, we simulate 10,000 scenarios for equity returns and interest rates, and we look into the evolution of the level of affordable income over the accumulation phase. As argued before, this indicator is more relevant than the absolute performance of the strategy in the retirement financing context. Formally, we calculate a “funding ratio,” defined here as the ratio of the current level of affordable income to the initial level of affordable income. This quantity is independent from the capital invested in the strategy and it measures the performance of the strategy relative to the retirement bond price. It would be constant at 100% for a portfolio fully invested in the GHP, and it grows above 100% if affordable income increases. In order to isolate the effect of the investment strategy, we assume in these simulations that no further contributions take place after inception.

Exhibit 4 reports a series of ex-ante indicators on the distribution of future funding ratios. To obtain these numbers, assumptions must be made on the dynamics of returns and risk factors impacting prices. We simulate the returns on an equity index by setting its annual volatility to 16.2% and its Sharpe ratio to 0.395, two values that are consistent with long-term forecasts and return estimates for the S&P 500 index. The bond component of the target-date fund is modeled as a portfolio with 6.4% volatility and 0.234 Sharpe ratio, and the GHP of the risk-controlled strategy replicates the returns of the retirement bond for an individual who retires in January 2038. This retirement horizon is a proxy for the discounted value of future cash flows given the current term structure of interest rates.

For parsimony, we assume a one-factor interest rate model, the parameters of which are calibrated to historical series of U.S. zero-coupon rates spanning the period from January 1998 through January 2018. 9 With the estimated parameters, the GHP has a volatility of 5.4% on average (decreasing over time as duration decreases) and a mean return of 3.05%. We emphasize that these parameter values are only needed to simulate future scenarios, but that they are not involved in the implementation of the GBI strategy.

When analyzing the results displayed in Exhibit 4, it appears that risk-managed target-date GBI retirement solutions are comparable to conventional target-date funds in terms of aspirational levels of funding. On the other hand, standard forms of target-date funds are unable to reliably secure annual losses to the specified level of 20%, with a 16.1% probability of experiencing at least one loss above this threshold over the period, when the GBI strategy reaches the objective of securing 80% of the initial annual funding ratio in all scenarios. 8

In the most extreme negative scenario in our simulations, the worst loss in terms of funding ratio for the target-date fund exceeds 35%, while it does not exceed the 20% limit set as an essential goal for the GBI strategy. Interestingly, realistic improvements to the PSP, which can be obtained by shifting from a cap-weighted index to a well-diversified portfolio of smart factor indexes, would lead to an extremely significant increase in the probability for investors to achieve their target levels of replacement income. For example a 200% increase in purchasing power can be obtained with close to 80% probability (78.1% given our parametric assumptions) for the GBI strategy with an improved PSP, to be compared with about 50% probability for both the target-date fund and the GBI strategy with a poorly diversified cap-weighted equity portfolio.

Mass customization in retirement investing

Goal-based investing principles can be used to effectively address the retirement investing problem by allowing investors to customize their retirement policy (for example, from age 55 to 65) to secure minimum levels of replacement income for a fixed period of time (for example, 15 years) in retirement, and levels of replacement income with attractive probabilities. At retirement date (for example, at age 65), an investor may decide on how to split the available surplus in two components, one dedicated to securing more replacement income for the early stage of decumulation and one dedicated to purchasing deferred inflation-linked late-life annuities to take care of tail longevity risk above and beyond for the late stage of retirement.

It is only recently that the emergence of the goal-based investing paradigm has effectively allowed for the development of such mass-customized investment solutions to individuals (see Martellini and Milhau (2017) for a detailed analysis). Mass-customization is facilitated by the convergence of powerful forces. On the one hand, production costs are strongly reduced, due to the emergence of smart factor indexes as cost-efficient alternatives to active managers for risk premia harvesting. On the other, distribution costs are also bound to go down as the trend towards disintermediation is accelerating through the development of FinTech and robo-advisor initiatives.

As many investors are not sufficiently knowledgeable about the investment landscape, or lack the ability to manage their funds, mass customization is essential to extend access to such mass-customized solutions to individuals. Mass customization in retirement investing is about designing retirement solutions tailored to individual preferences and circumstances. Traditional retirement solutions are the result of mass-assembly processes and mass-customization is about the reverse engineering of such mass-production of retirement solutions to cater for individual needs.

References


8 In implementation, it would also be useful to make it a function of market conditions, based on the finding that higher volatilities and lower expected returns should imply lower multiplier values, and that conversely, lower volatility and higher expected returns should result in higher multiplier values.
9 Details on the calibration procedure can be found in Martellini and Milhau (2017).
10 In robustness checks, we have found that some gap risk arises when the GBI strategy is rebalanced quarterly, as opposed to monthly. On the other hand, gap risk is limited in probability (0.2%) and in severity (worst annual loss at 23.4%).
Predicting Risk Premia for Treasury Bonds: The ERI Risk Premium Monitor

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EXHIBIT 1

Predicting Excess Returns

<table>
<thead>
<tr>
<th>Sub-period</th>
<th>Simple Slope</th>
<th>New-Generation</th>
<th>Old-Generation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1955-1986</td>
<td>0.04</td>
<td>0.04</td>
<td>0.04</td>
</tr>
<tr>
<td>1987-2014</td>
<td>0.59</td>
<td>0.56</td>
<td>0.49</td>
</tr>
</tbody>
</table>

EXHIBIT 2

Average excess returns and various return-predicting factors

<table>
<thead>
<tr>
<th>Period</th>
<th>Simple Slope</th>
<th>New-Generation Factors</th>
<th>Old-Generation Factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st half 2000-05</td>
<td>0.05</td>
<td>0.15</td>
<td>0.05</td>
</tr>
<tr>
<td>2nd half 2000-05</td>
<td>-0.10</td>
<td>-0.25</td>
<td>-0.10</td>
</tr>
</tbody>
</table>

Why Risk Premia Matter

Investors in the Treasury market often observe an upward-sloping yield curve. This means that, by assuming ‘duration risk’, they can vary their investment at a higher yield than their funding cost. Yet, if the steepness of the yield curve purely reflected expectations of future rising rates, no money could on average be made from this strategy. This prompts the obvious question: When does the steepness of the yield curve simply reflects expectations of rising rates, and when does it embed a substantial risk premium?

The investment relevance of being able to answer these questions is clear. Take, for instance, a bond manager whose performance is assessed against a Treasury benchmark. Her main strategic investment choices boil down to deciding whether to be long or short duration with respect to the benchmark. Knowing how well she is compensated for taking this duration risk is key to her long-term performance. Or take a multi-asset portfolio manager. Deciding the relative portfolio weights among the different risk factors hinges in great part on the time-varying compensation attaching to these different factors.

In all these cases, and in many more, being able to estimate in a reliable and robust manner the risk premium attaching to yields is key to successful investing. It is for this reason that the EDHEC-Risk Institute is launching the ERI Risk Premium Monitor: a robust tool to extract from market and monetary-policy information a state-of-the-art estimate of the risk premium. The rest of this note explains how this task is achieved, and the theoretical underpinnings of the analytical tools used for the task.

Predicting Excess Returns

What predicts excess returns in Treasury bonds? And how much can one explain? Until recently, the answers to both questions used to be: ‘the slope’, and ‘rather little’, respectively. States of the world characterized by a steep upward-sloping yield curve used to be considered indicators of positive expected excess returns. The degree of predictability was however modest (with R² of the regression of the predicted and realized excess returns never exceeding 20%). To understand why the slope was deemed to be a good predictor of excess returns consider Exhibit 1.

Now, recessionary periods are associated with the monetary authorities cutting rates and therefore engineering an upward-sloping yield curve. It is also natural to assume that and their predictions.

<table>
<thead>
<tr>
<th>Period</th>
<th>Simple Slope</th>
<th>New-Generation Factors</th>
<th>Old-Generation Factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>1979: Q1-1981: Q2</td>
<td>-1.06</td>
<td>-1.13</td>
<td>-1.23</td>
</tr>
<tr>
<td>1993: Q2-1995: Q3</td>
<td>-0.79</td>
<td>-0.86</td>
<td>-0.86</td>
</tr>
<tr>
<td>2004: Q2-2006: Q3</td>
<td>-1.52</td>
<td>-0.96</td>
<td>-0.58</td>
</tr>
</tbody>
</table>

Of excess returns sometimes produce much higher R². Why is this the case? And what is the economic significance of the new, more complex, factors?

The motivation of the question can be readily understood by looking at Exhibit 2 (and 3), which focus on the predictions made by the old- and new- generation factors.

More precisely, Exhibit 2 shows the realized average excess returns, and the excess returns predicted by the slope and other ‘new-generation’ return-predicting factors. While all these predictions are all strongly correlated it is clear that the new-generation factors add a substantial twist to the slope story.

Exhibit 3 makes this intuition clearer by showing the differences between the prediction produced by the slope, and the predictions produced by the new- generation factors (in-sample analysis). Despite the fact that the new return-predicting factors are constructed following very different prescriptions, what is added on top of the slope predictions is remarkably similar.

This qualitative analysis therefore prompts the following questions:

1. Are these ‘extra predictions’ informative, or, as Bauer and Hamilton (2015) argue, are they just a result of over-fitting?
2. Why do such apparently different return-predicting factors produce such similar incremental predictions (with respect to the slope predictions)?
3. What is their financial and economic interpretation?

A full answer would take too long a detour (see, eg, Rebonato (2018)). We can however summarize the main findings as follows.

The first insight is linked to the power spectrum of excess returns: one can easily see both low-frequency (business-cycle) components (well captured by the ‘old’ slope factor), but also a much higher frequency contribution, that requires higher principal components to be captured. It is in part because of its ability to capture these high-frequency components that a factor such as the Cochrane-Piazzesi fares better than the slope by itself.

This is shown in Exhibits (4) and (5). The first exhibit shows that at all investment horizons there are important contributions from both low (‘business-cycle’) and high-frequencies components. When we look at Exhibits (5a) and (5b), which show the frequency spectrum of the slope factor and of a ‘new-generation’ factor, we note how the slope recovers the low frequency peaks of the excess returns, but completely misses the medium and high-frequency components. Contrast this with the power spectrum of the 5-year excess returns and one of modern factors, which displays a remarkable match across all frequencies.

The second ‘modern’ insight alluded to above suggests that a large fraction of return predictability comes from detecting the cyclical stringing of yields from a long-term fundamental trend. Once an effective decomposition of the yield dynamics into trend and cycle is carried out, one finds that the different degrees of mean reversion of the various return-predicting factors explain the different degrees of excess returns predictability very well.

Why do both of these two different ‘types’ of factors help the prediction of excess returns?

We propose that two distinct financial mechanisms can explain excess returns: the first, ie, the one associated with low-frequency changes in excess returns, is linked with changes in risk aversion with business-cycle periodicity. As for the second financial mechanism, associated with higher-frequency cycles, we suggest that it is coming from the actions of pseudo-arbitrageurs who bring back in line with fundamentals the level and slope of the yield curve. These deviations have a much quicker mean-reversion, and are therefore associated with the higher-frequency components of the excess return spectrum.

The full picture is more complex, but one can the key two insights are that the frequency components of excess returns and their mean reverting properties give us a very effective procedure to construct powerful and very parsimonious return-predicting factors: in order to predict excess returns we need a good frequency match (across high and low frequencies), and a good match of the speed of mean reversion. When these two conditions are satisfied, a number of similarly (and highly) effective and robust factors can be built almost by inspection. The new factors are parsimonious (they only require one slope-like component and one cycle-like component), intuitively understandable (thanks to the financial interpretation offered above) and highly effective (both in-sample and out-of-sample they predict as well as, and often better than, the Cochrane-Piazzesi or the Cieslak-Povala Factors).

1. The differences between the prediction of average excess returns produced by the slope, and the predictions produced by the new-generation factors (in-sample analysis, US data).

EXHIBIT 3

EXHIBIT 4

EXHIBIT 5

2. No use is made of any information about the level of market yields: clearly, an estimate of, say, a –3% term premium has a different degree of ex ante plausibility depending on whether the corresponding market yield is, say, at 6% or 2%.

Traditionally, the ‘other’ route to estimating risk premia...
has been via the use of arbitrage-free affine term-structure models. Unfortunately, affine models do incorporate information about the level of market yields, and do ensure absence of arbitrage, but rarely do they have the flexibility to capture the rich information conveyed by the statistical analysis. Both approaches are useful, but neither tells the whole truth. The ERI Risk Premium monitor exploits the relative strengths of the two approaches and tries to overcome their weaknesses. It does so by complementing the predictions from the statistical estimate with the assessment of the risk premium coming from a member of the family of affine models described in Rebonato (2017). The chosen model uses as state variables the short rate, its own stochastic reversion level and the market price of risk:

\[ \begin{align*}
\frac{d\theta_t}{\sigma_r} &= \theta_t \left( \theta_0 - \theta_t \right) dt + \sigma_d z_t^d \\
\frac{d\theta_t}{\sigma_r} &= \theta_t \left( \theta_0 - \theta_t \right) dt + \lambda \sigma_d z_t^d + \sigma_d z_t^d \\
\lambda_t &= \lambda_t \left( \lambda_0 - \lambda_t \right) dt + \sigma_1 z_t^d,
\end{align*} \]

where \( \theta \) and \( \lambda \) are the time-

rate, of its instantaneous reversion level (the ‘target rate’) and the market price of risk, respectively; \( \sigma_r \) and \( \sigma_1 \) are the associated volatilities; \( \theta_0 \) and \( \lambda_0 \) are the reversion levels of the ‘target rate’ and of the market price of risk, respectively; and the increments \( dz^d \), \( dz^d \) and \( dz^d \) suitably correlated. The model is fully specified once the initial state, \( \theta_0 \), \( \lambda_0 \) and \( \lambda_0 \) is given. The reader is referred to Rebonato (2017) for the financial motivation of the model, and for a detailed description of its performance. For our purposes, the important observation is that the information about the P-measure path of the Fed funds (the ‘short rate’) comes from the forward guidance (the ‘blue dots’) provided quarterly by the Fed. See Exhibit (6).

When the two sources of information are combined, we obtain for the 10-year term premium the composite robust estimates shown in Exhibits (7) and (8).

As Exhibit (7) shows, the correlation among the statistical and the model-based estimate are above 90% for all the models. This is remarkable, considering how different the approaches and the sources of information are.

This congruence gives us confidence about the robustness and the reliability of the combined approach.

CONCLUSION

In this note we have given a glimpse of the latest and most exciting research strands carried out in the academic world in general, and at the EDHEC-Risk in particular, about the robust estimation of the yield risk premia. The predictions about the term premia for various yield maturities of the US Treasuries will be regularly provided, together with more formal research papers on these and related topics. Much work remains to be done, for instance by looking at different currencies, and at related asset classes. However, we believe that the present offering can already be of real practical use and interest for practitioners and for academics.

References


12 To simplify the analysis, and in line with standard findings (see, e.g., Cochran & Piazzesi 2005, 2008; Adrian, Crump & Moore 2013), the model assumes that investors only seek compensation for the uncertainty about the level of rates, which we proxy in our approach as the long-term reversion level of the reversion level.
Live is Better

Since 2013, with the Smart Beta 2.0 framework, EDHEC-Risk Institute has created Scientific Beta multi-smart-factor indices that are well diversified and exposed to rewarded factors. These indices have a robust live track record with annualised outperformance of 2.14% and an improvement in Sharpe Ratio of 45.71% compared to their cap-weighted benchmark.¹

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

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¹ The average live outperformance and improvement in Sharpe Ratio across all Scientific Beta developed regions of Scientific Beta Multi-Beta Multi-Strategy (Equal Weight and Equal Risk Contribution) indices is 2.11% and 46.16% for the outperformance and 45.27% for the improvement in Sharpe Ratio. This live analysis is based on daily total returns in the period from December 20, 2013 (live date) to December 31, 2017 for all diversified multi-strategy indices that have more than 3 years of track record for all available developed world regions – USA, Eurozone, UK, Developed Europe, Developed Europe ex UK, Japan, Developed Asia Pacific ex Japan, Developed ex UK, Developed ex USA and Developed. The benchmark used is a cap-weighted portfolio of all stocks in the respective Scientific Beta universes.

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Key Learning Objectives

> Learn how to perform factor investing and risk allocation
> Develop an understanding of strategic asset allocation in the presence of liability constraints
> Assess how to overcome effect of estimation error by imposing better constraints
> Understand how to implement liability-driven investment solutions with cash and derivatives instruments
> Learn about goal-based investing strategies in institutional and private wealth management
> Identify affordability conditions for essential and aspirational goals

> Discuss implementation and mass customization challenges for individual investment solutions
> Explore novel welfare-improving forms of investment solutions
> Discuss an application to the design of efficient retirement solutions
> Learn the evidence on return predictability
> Discuss the models, techniques and applications of active multi-asset allocation strategies
> Review the evidence on identifying active managers who are most likely to outperform

A cocktail party is scheduled during this 3-day event to immerse you in the Yale campus experience

For further information and registration, please contact Caroline Prévost, EDHEC-Risk Institute at: yalesom-cri@edhec-risk.com or on: +33 493 183 496.