

# Ten Misconceptions about Smart Beta

Analysing common claims on performance drivers,  
investability issues and strategy design choices

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# Executive Summary

Smart Beta strategies, as one of the strongest growth areas in investment management recently, have established a space in between traditional capitalisation-weighted (or "cap-weighted") passive investments and traditional (proprietary and discretionary) active management. Perhaps unsurprisingly, Smart Beta has drawn fierce criticism from both advocates of traditional active management and of traditional passive management. In a nutshell, proponents of proprietary active strategies complain that Smart Beta is not active enough while proponents of traditional cap-weighting say that Smart Beta is not passive enough. Smart Beta providers have not only responded to such criticism, but have also been vocal about the benefits of their respective approaches, without necessarily agreeing with one another. Such debates have too often led to misconceptions. The objective of this paper is to review ten common but mistaken claims about Smart Beta, and to shed light on the underlying issues.

## Part I: Performance Drivers

### 1. The Hiding Game: "Smart Beta generates alpha"

Smart Beta aims at outperforming standard cap-weighted market indices on a risk-adjusted basis (higher Sharpe ratio for example). Some in the industry claim that Smart Beta is thus a way of generating alpha. However, we argue that a careful distinction should be made between returns due to systematic portfolio construction, and those due to manager skill. Systematic portfolio construction approaches falling under the Smart Beta umbrella may add value relative to broad-market capitalisation weighted indices due to three distinct components: i) exposure to additional rewarded factors beyond the market factor, ii) improved diversification

targeted at avoiding exposures to unrewarded risks, and iii) risk-based multi-factor allocation targeted at delivering explicit risk objectives. None of these approaches can be assimilated with alpha, understood as performance attributable to manager-specific skill or attributable to an ability to exploit short-term mispricing in the market or a capacity to time the market or particular categories of stocks. While Smart Beta providers may be tempted to claim that their strategies deliver alpha - in order to justify higher fees for example - the fact that they do not is actually reassuring for users of Smart Beta. Indeed, these three sources of performance can be tapped systematically based on consensual insights and a vast amount of academic evidence, while the search for alpha will continue to be more of an art than a science. Moreover, it appears incoherent to us to criticise active (alpha seeking) managers for their inability to beat the market persistently by timing the market or by picking stocks and at the same time to suggest that generating alpha can be done by systematic strategies which often rely on backward looking accounting data. Looking for alpha in Smart Beta is not likely to add much value and may instead lead to considerable risk of underperformance.

### 2. The Monkey Portfolio Claim: "Anything beats cap-weighted market indices"

There are assertions that Smart Beta strategies add no value beyond what could be achieved by randomly weighting securities. The ultimate "proof" of this proposition is the claim that smart beta indices produce even better outperformance when one inverts their weights. However, careful analysis shows that Smart Beta strategies are not created equal, and that both factor exposures and diversification approaches matter. Inverting Smart Beta strategies

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tilted towards factors associated with long-term over-performance produces long-term performance and risk-adjusted performance that are significantly lower than what the original strategies deliver. Smart Beta strategies are not monkey portfolios and investors cannot rely on the belief that any alternative weighting will deterministically improve performance. Investing in Smart Beta strategies instead requires due diligence covering the factor tilts and diversification mechanisms employed if an investor is to select a strategy that corresponds to its investment objectives and beliefs. Claiming that all Smart Beta strategies are identical can be seen as an attempt to discourage thorough analysis of alternative solutions in terms of robustness and risks. Proponents of monkey portfolio arguments are perhaps just creating a smokescreen to hide poor live performance of the products they promote but do a disservice to investors who are interested in understanding the risks and the robustness (or lack thereof) of Smart Beta performance across different types of strategies.

### 3. The Value and Size Myth: "All Smart Beta performance comes from value and small cap exposure"

Some argue that once one deviates from selecting and weighting stocks on the basis of their market value, as is done in capitalisation-weighted indices, one necessarily introduces positive value and size factor exposures. However, when analysing commonly employed Smart Beta strategies, it appears that they have exposure to multiple factors beyond Value and Size. Indeed, Smart Beta strategies can be dominated by and derive the bulk of their outperformance from these additional factor exposures. This finding may not be surprising, and is fully consistent with the academic literature, which has

documented the importance of various equity risk factors beyond Value and Small Size.

Moreover, while alternative weighting schemes, by deviating from standard cap-weighted indices, indeed lead to the introduction of implicit factor exposures (notably Small Size), using alternative weighting schemes without providing any option to also explicitly target factor exposures corresponds to a first generation Smart Beta approach (Smart Beta 1.0). Such approaches are rather limited as they do not allow for an explicit choice of risk factor exposures. The Smart Beta 2.0 approach allows exposures to be chosen by constructing Smart Beta strategies in two independent steps: the selection of constituents and the choice of a diversification-based weighting scheme. Within this framework, it is straightforward to correct the implicit tilts of weighting schemes through the prior selection of stocks with appropriate characteristics.

### 4. The Rebalancing Fantasy: "Smart Beta outperforms because it trades against mean reversion"

A straightforward difference between cap-weighted indices and Smart Beta strategies is that weights are adjusted at rebalancing dates rather than left to drift with the price evolution of constituents. Some have argued that the performance of Smart Beta strategies is explained fully by this rebalancing.

However, this claim does not stand up to scrutiny. An analysis of buy-and-hold portfolios versus portfolios that are rebalanced at different frequencies shows that whether or not one generates increased performance from rebalancing in fact depends on the return behaviour of the assets in the menu. Rebalancing may

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or may not lead to improved performance over buy-and-hold strategies depending on the asset menu and the time period. Even if positive rebalancing effects exist, it is uncertain that Smart Beta strategies capture such effects.

Moreover, contrary to the idea that rebalancing drives performance, analysis suggests that rebalancing an equal-weighted strategy more often does not necessarily improve performance. And both short-term and long-term reversal effects are empirically unimportant in explaining the performance of a broad range of Smart Beta strategies.

Of course, rebalancing may be important, notably to maintain diversification or to maintain target factor exposures. However, rebalancing in itself is not an empirically documented source of the performance of Smart Beta strategies.

Promoting a false rebalancing effect on the back of the well-documented mean reversion effect at the asset class level (see Poterba and Summers (1988) or Fama and French (1988)) is dangerous because it suggests that poor performance of certain strategies, which may be due to a lack of robustness, is just the price to pay for bright future performance. Here again, such misconceptions regarding the sources of performance of Smart Beta can have serious consequences for investment decision making.

### Part II: Investability Hurdles

#### 5. The Liquidity Concern: "Smart Beta requires holding positions in highly illiquid stocks"

Portfolio liquidity is one of the key considerations in investment management. Smart Beta strategies have been criticised

for increased liquidity risks and some have asserted that their outperformance is due to capturing an illiquidity premium. We have shown that, while naively implemented Smart Beta strategies may obviously suffer from much reduced liquidity, the outperformance of Smart Beta strategies can be maintained while ensuring high liquidity and ease of implementation. Our empirical results suggest that selecting increasingly liquid stocks and introducing further liquidity-enhancing rules improves liquidity and reduces implementation issues; at the same time, doing so preserves the bulk of the outperformance benefits of Smart Beta approaches. Observing the significant outperformance of Smart Beta indices that use such implementation rules suggests that target factor exposures and alternative weighting schemes, not the capture of an illiquidity premium, are the main drivers of the performance of Smart Beta strategies.

#### 6. The Turnover Critique: "Smart Beta necessarily leads to high turnover"

Smart Beta strategies generate turnover from periodic rebalancing required to maintain strategy weights. This has led to claims that Smart Beta will incur excessive turnover. However, while Smart Beta strategies will necessarily incur higher turnover than cap-weighted market indices, there are well known techniques to keep turnover within reasonable bounds while maintaining the outperformance potential. There is ample empirical evidence that many Smart Beta strategies provide outperformance after suitably designed turnover mitigation strategies have been applied. Investors should thus analyse the turnover mitigation aspects of these strategies and request transparency on incurred turnover from providers. Indeed, thorough analysis of the turnover aspects of a specific strategy that may be of interest in a given investment

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context seems more appropriate than reliance on blanket criticism of Smart Beta.

### 7. The Crowding Hypothesis: "If everyone knows about Smart Beta the benefits will disappear"

There are concerns that, as Smart Beta strategies gain popularity, flows into these strategies will ultimately cancel their benefits.

However, such claims are rarely based on solid empirical evidence. And the academic literature has not only documented risk premia for the standard factors but has also provided theoretical explanations for persistence, notably if factors are compensation for taking on additional types of risk. Moreover, precautions against crowding risks can be taken by proper implementation of factor investing and Smart Beta indices. In particular, the best precaution against crowding seems to be diversification. If investors spread their Smart Beta investments across several strategies, and several factors, there should not be crowding in a single strategy.

Of course, it is possible that Smart Beta and factor strategies can be subject to adverse effects due to a wide following but one can only conclude that this is the case if there is evidence for it. Simply referring to losses in a given strategy, however, is not an evidence of crowding. Moreover, if one is concerned about potential crowding, the immediate concern should be to i) hold well-diversified rather than concentrated strategies, and ii) spread out over many different strategies. In addition, the concerns over "crowding" issues underline the importance of clarifying investment beliefs and understanding the rationale for a given factor premium. The confusion about factor crowding can have negative consequences for investors.

Such confusion may lead investors to invest in novel exotic factors which, in the end, are not rewarded and expose them to heightened data-mining risks. In fact, exotic new factors are typically justified on the basis of short-term data and use proprietary complex scoring approaches to claim that such factors are less replicable and therefore less prone to crowding. That said, a necessary consequence is that these factors are often over-fitted, and resulting from model mining and will not be robust out of sample. Confusion about crowding can also help to promote false ideas about the timing capacity of fundamentally weighted approaches or their capacity to identify underpriced stocks, which has nothing to do with evidence-based investing through factors but much to do with ad hoc storytelling approaches and with a low-tech, and probably a low-efficiency approach to active management.

## Part III: Strategy Design Choices

### 8. The Concentration Fallacy: "A good factor index should provide a strong tilt to the desired factor"

Providers commonly argue that an index must have a strong tilt toward a factor to produce good performance. Indeed, factor indices are a potentially value-adding tool. Investors can expect benefits from relying on indices which tilt towards well-documented factors that offer sizeable and repeatable return benefits over long investment horizons. However, when aiming to implement the insights from empirical asset pricing, one should remember a more fundamental insight from financial theory, i.e. that diversifiable risk commands no premium. Our results suggest that index construction approaches which build diversified portfolios for a given factor-based stock selection are exposed to less unrewarded risk, outperform their

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concentrated counterparts and allow investors to avoid the strong underperformance related to bets on the wrong idiosyncratic returns, which can be the consequence of a sole focus on creating strong exposure to factors. Considering these two aspects – namely factor tilts and specific risk diversification – should be an integral part of a sensible factor index design methodology.

Moreover, factor indices are indices after all, and thus should be implementable with ease and low turnover. Our results suggest that narrowing stock selections in an effort to improve portfolio-wide factor scores leads to high turnover levels and investability hurdles which are not compensated by significant performance advantages. By comparison, applying a diversification-based weighting scheme to broad stock selections produces significant improvements of performance with only modest increases in turnover.

### 9. The Factor Fishing Licence: "A good factor index requires a sophisticated scoring approach"

Product providers frequently claim that customisation by innovative factor definitions is the key to Smart Beta strategy design. Indeed, many indices offered by product providers rely on sophisticated proprietary variable definitions to derive factor scores – these typically involve combinations of multiple metrics with various adjustments.

Given the strong emphasis providers put on the "academic grounding" of their factor strategies, it is surprising that they then choose to implement products that take extreme liberty with academic factor definitions and do not respect the key academic principle of parsimony.

Possible out-of-sample degradation of most of the strategies selected on the basis of favourable in-sample performance is a real risk to investors. Strategies that rely on promising in-sample performance rarely deliver on their promises out-of-sample.

With the advance of modern data processing tools and the ever-increasing amount of data, the temptation to mine for attractive in-sample results is higher than ever before. Investors should carefully evaluate the relevance of back-tests and assess the reliability and robustness of the results of any portfolio to avoid the trap of data-mining.

### 10. The Factor Purity Argument: "A good factor index needs to isolate exposure to the target factor"

Some argue that a factor index should not only provide the exposure to an intended factor but also neutralise any exposure to other factors. However, purity is difficult to achieve at the individual factor index level. When trying to create pure factors, one ends up with formidable implementation challenges. However, this is not necessarily a problem. For example, the standard Fama and French or Carhart factors are neither designed to be pure nor to be uncorrelated in the data. This in no way questions the academic relevance of these factors as being useful in explaining the cross section of expected stock returns nor their practical relevance as useful sources of additional returns relative to those delivered by broad equity market exposure. Likewise, the fact that commonly used factor indices are not pure does not question their usefulness for investment portfolios, given that factor purity is not likely to be an objective in most investment contexts. In the end, a focus on purity is rarely warranted and will necessarily come at the expense of diversification and ease of implementation,

which are first-order issues with factor indices.

### Conclusions

The objective of this paper is to provide perspective on common misconceptions by examining conceptual considerations and empirical evidence. The analysis of the ten items in this paper shows that, more often than not, superficially convincing claims about Smart Beta strategies stand on shaky foundations. Our analysis also shows that challenging conventional wisdom by reviewing the extant academic literature and empirical evidence may perhaps lead to more balanced conclusions and a more nuanced understanding of the benefits and risks of Smart Beta strategies.

Many of the misconceptions debunked in this paper correspond to over-generalisations which fail to acknowledge that the term Smart Beta covers a vast variety of strategies with potentially very different properties. In a nutshell, our analysis cautions against such oversimplification and calls for a rigorous and detailed analysis of Smart Beta strategies.

# 1. Introduction

Smart Beta strategies have been one of the strongest growth areas in investment management over the past decade. Smart Beta has been establishing a space in between traditional (cap-weighted) passive investments and traditional (proprietary and discretionary) active management. Perhaps unsurprisingly, Smart Beta has drawn fierce criticism from both advocates of traditional active management and of traditional passive management. In a nutshell, proponents of proprietary active strategies complain that Smart Beta is not active enough (see for example Yasenchak and Whitman (2015)<sup>1</sup>) while proponents of traditional cap-weighting say that Smart Beta is not passive enough (see for example Philips et al. (2015)<sup>2</sup>). Smart Beta providers have not only responded to such criticism, but have also been vocal about the benefits of their respective approaches, without necessarily agreeing with one another. While such debates sometimes allow facts to be established, they have too often led to misconceptions. The objective of this paper is to review ten common but mistaken claims about Smart Beta and shed light on underlying issues.

This paper addresses these ten claims in turn. Misconceptions 1 to 4 relate to the sources of outperformance of Smart Beta. Misconceptions 5 to 7 relate to investability hurdles for Smart Beta strategies. Misconceptions 8 to 10 concern specific Smart Beta index design choices.

1 - Yasenchak, R. and P. Whitman. 2015. Understanding the Risks of Smart Beta and the Need for Smart Alpha. Intech Janus White Paper. Available at: <http://ow.ly/WEKQ2>.  
2 - Philips, C., D. Bennyhoff, F. Kinniry, T. Schlanger and P. Chin. 2015. An Evaluation of Smart Beta and other Rules-based Active Strategies. Vanguard White Paper. Available at: <https://advisors.vanguard.com/iwe/pdf/ISGSBA.pdf>.

# Part 1: Performance Drivers

# 1) The Hiding Game: "Smart Beta Generates Alpha"

## Reviewing the Proposition

Smart Beta aims at outperforming standard cap-weighted market indices on a risk-adjusted basis (higher Sharpe ratio for example). Some in the industry claim that Smart Beta is thus a way of generating alpha. For example, Investopedia<sup>3</sup>, a common resource for the industry, claims that "The goal of Smart Beta is to obtain alpha." Research Affiliates<sup>4</sup>, a Smart Beta index provider also mentions that Smart Beta is all about alpha: "*Smart Beta actually can mean something useful: a smarter way for investors to buy beta with alpha. After all, if one can find a more reliable alpha, and pay less for it, that would be pretty smart.*" Similarly, Bender et al. (2014)<sup>5</sup> state that "...a handful of risk-premia indices can account for a substantial portion of alpha."

Alpha is a term used to describe returns which are unexplained by systematic risk exposure and attributable to skill. Traditionally returns above those of broad-market indices were equated with alpha. This view evolved with the diffusion of the Capital Asset Pricing Model (CAPM), the father of asset pricing models, which derived a linear relationship between expected returns and systematic risk, which was fully captured by the covariation of assets with an all-encompassing, capitalisation-weighted, "market" portfolio. In the context of the CAPM, above market returns are explained by higher betas, that is systematic variability above that of the average represented by the market portfolio (beta is the covariance between the returns of the asset and the returns of the market portfolio standardised by the variance of the market portfolio). As it is easily diversified by grouping assets into a portfolio, non-systematic variability,

also known as specific risk receives no compensation. Assuming that broad-market cap-weighted indices are good proxies of the theory's market portfolio, any strategy that beats the market index while having a beta lower than one (or more generally, any strategy that returns more than what its beta commands) generates alpha, i.e. an additional amount of return which is not explained by the exposure to the market factor. Such an understanding of alpha, while still being prevalent amongst practitioners, is inconsistent with the current state of development of asset pricing. Since the development of the CAPM by Sharpe (1964<sup>6</sup>), Lintner (1965a<sup>7</sup>), Mossin (1966<sup>8</sup>) and Treynor (1962<sup>9</sup>), finance has indeed progressed, in particular through contributions of Nobel prize winning economists, and developed richer asset pricing models which allow for multiple priced risk factors based on equilibrium (Merton (1973<sup>10</sup>)) or absence of arbitrage (Ross (1976<sup>11</sup>)) arguments. Empirical asset pricing models based on such theoretical insights include factors in addition to the market factor such as size, valuation, and momentum, as proposed in the Carhart (1997) extension of the Fama and French (1993<sup>12</sup>) model, and additional factors such as investment, profitability, or volatility in further extensions of this approach. Note that in the presence of multiple priced risk factors, the optimal portfolio is not defined in mean-variance efficiency terms but instead in terms of multifactor efficiency portfolio (see Fama (1996<sup>13</sup>) and Cochrane (1999<sup>14</sup>)) - hence even if capitalisation-weighted market indices corresponded to the optimal portfolio of mean-variance theory, they would not be necessarily optimal in a multifactor world.

3 - Smart Beta entry on Investopedia, <http://www.investopedia.com/terms/s/smart-beta.asp>

4 - Arnott, R. and E. Kose. 2014. What 'Smart Beta' Means to Us. Research Affiliates Fundamentals.

5 - Bender, J., P. B. Hammond and W. Mok. 2014. Can Alpha Be Captured by Risk Premia? *Journal of Portfolio Management* 40(12): 18-29.

6 - Sharpe, W.F. 1964. Capital Asset Prices: A theory of Market Equilibrium under Conditions of Risk. *The Journal of Finance* 19(3): 425-442.

7 - Lintner, J. 1965a. The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *The Review of Economics and Statistics* 47(1):

13-37 and Lintner, J. 1965b. Security Prices, Risk and Maximal Gains from Diversification. *The Journal of Finance* 20(4): 587-615.

8 - Mossin, J. 1966. Equilibrium in a Capital Asset Market. *Econometrica* 34(4): 768-783.

9 - Treynor, J. 1962. Toward a Theory of Market Value of Risky Assets. Manuscript.

10 - Merton, R. C. 1973. An Intertemporal Capital Asset Pricing Model. *Econometrica* 41(5): 867-887.

11 - Ross, S. 1976. The Arbitrage Theory of Capital Pricing. *Journal of Economic Theory* 13(3): 341-360.

12 - Fama, E. F. and K. R. French. 1993. Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics* 33(1): 3-56.

13 - Fama, E. F., 1996. Multifactor Portfolio Efficiency and Multifactor Asset Pricing. *Journal of Financial and Quantitative Analysis* 31(4): 441-465.

14 - Cochrane, J.H., 1999. Portfolio Advice for a Multifactor World. *Economic Perspectives* - Federal Reserve Bank of Chicago 23(3): pp. 59-78.

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Such progress forms the basis of Smart Beta approaches which try to generate outperformance relative to broad-market cap-weighted indices by taking on exposures to long-term rewarded risk factors beyond the market factor. It would thus be indeed surprising if promoters of Smart Beta who found their approaches on the existence of such multiple factors forgot to account for exposure to these factors when measuring alpha. To the extent that multiple factors are priced in equity markets, a higher return than commanded by exposure to broad market risk may be explained by differences in exposure to additional sources of systematic risk. Returns which are explained by such exposures or "factor betas" are a compensation for taking on additional types of risks. Moreover, they can be captured through systematic strategies which are widely known and can be implemented in a mechanistic manner. In this sense, such returns are neither "unexplained" nor attributable to any form of skill. Therefore, such extra returns lead to outperformance relative to a broad market index but cannot be qualified as alpha.

For example, if a standard and systematic value-tilted Smart Beta strategy outperforms the market index, this is due to its value exposure or value beta, not to any alpha. Likewise, if a fixed income portfolio outperforms the broad bond market index by loading more heavily on bonds with higher credit risk, this is not alpha but capture of additional returns compensating additional credit exposure or higher "credit beta".

### Sources of Value Added in Smart Beta

When employing more recent empirical asset pricing models that recognise multiple priced factors, outperformance

relative to the market of strategies that simply tilt towards additional risk factors will be largely explained by exposures to the relevant factors. Nevertheless, Smart Beta strategies may use two different approaches to improve risk-adjusted investment outcomes relative to simple tilts towards rewarded risk factors. These extra sources of risk-adjusted returns can be tapped without relying on active management skills and as such do not constitute true alpha.

First, Smart Beta strategies may aim to provide better diversification for a given factor tilt. It is a fact that asset pricing models establish a linear relationship between exposure to a given risk factor and expected returns. In this context, one may be tempted to maximise exposure to this factor by concentrating a portfolio in a few stocks offering high factor exposure (and at the limit the single stock offering the highest factor exposure). However, such an approach will inevitably lead to taking on unrewarded risk, notably stock-specific risk, thus leading to inferior risk-adjusted returns. Factor investing and modern portfolio theory are not mutually inconsistent: factor investing does not require the use of inefficient portfolios. Smart Beta strategies may thus simultaneously exploit the benefits of tilting to rewarded factors and the benefits of constructing well-diversified portfolios. From a theoretical point of view, Fama (1996) and Cochrane (1999) underline that factor proxies should be mean-variance efficient. From an empirical point of view, Amenc et al. (2016<sup>15</sup>) provide evidence that well-diversified factor-tilted portfolios lead to improved risk-return properties relative to concentrated portfolios tilting towards the same factors. Well-diversified factor indices deliver improved risk-adjusted returns simply by reducing exposure to

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unrewarded risk through diversification. Such well-diversified factor tilted portfolio strategies consider not only the evidence on additional risk factors that has accumulated over the past forty years, but also respect the diversification principles derived from the work of Markowitz (1952)<sup>16</sup> and the opposition between systematic and specific risk introduced by Sharpe (1963)<sup>17</sup> as a practical solution to estimate parameters for the Markowitz model.<sup>18</sup> The key idea of well-diversified factor-tilted indices is to access the reward of exposure to systematic factors while diversifying away unrewarded risk (see Amenc et al. (2014)<sup>19</sup>). Such an approach cannot be equated with manager skill or superior information, and, in this sense, does not constitute alpha.

Second, Smart Beta strategies that tilt to a single factor but are already well-diversified in the sense of avoiding exposure to unrewarded risk, are nevertheless limited since they ignore the potential benefits of allocating to several factors. Multi-factor allocation approaches combine exposures to several rewarded factors. By exploiting the information on risk parameters, and in particular the correlation structure across factors, such approaches, in particular when they are implemented as dynamic strategies, allow for the improvement of risk-adjusted returns relative to static exposures to single factors. Moreover, such strategies allow to take into account specific objectives in a given investment context such as risk targets in terms of absolute or relative risk. Such approaches rely on information on risk parameters and investor objectives but do not aim to predict the future realisation of returns. They are not related to manager skill or alpha since they draw on factor allocation techniques which are entirely systematic and focus on using information on risk parameters.

Having discussed the various manners in which well-designed Smart Beta strategies can produce excess performance relative to capitalisation-weighted indices that does not constitute alpha, it is probably useful to indicate what alpha could skilled managers add to Smart Beta.

If the objective is to employ manager skill to generate alpha, one could target two sources of alpha. A first source would be to time the exposure to rewarded factors, implying tactical bets on the returns of long-term rewarded factors. For example, a given factor which is rewarded in the long term, may underperform in any given short-term period, say a calendar year, and a manager who has the skill of predicting such short-term returns could exploit such insights to generate alpha. Factor timing decisions are thus a potential source of alpha which one can qualify as alpha stemming from tactical allocation.

Moreover, a manager could try to make bets on unrewarded risks. For example, while there is no long-term reward to taking on stock-specific risk, a manager that has the capacity to predict company performance over the short run could take on such exposures temporarily to benefit from her stock-picking abilities. Timing factors and identifying stock-specific opportunities are likely more of an art than a science. Superior timing and selection skills are extremely rare and show little persistence; they are certainly not available from well-documented systematic Smart Beta strategies. If one wants to access such alpha, one needs to be able to identify skilful and persistent managers ex ante.

In the following exhibit, we provide a schematic overview of some of the properties of Smart Beta indices and compare them to both traditional active

16 - Markowitz, H. 1952. Portfolio Selection. *Journal of Finance* 7(1): 77-91.

17 - Sharpe, W.F. 1964. Capital Asset Prices: A theory of Market Equilibrium under Conditions of Risk. *The Journal of Finance* 19(3): 425-442.

18 - See Misconception No. 8 below in this document for further discussion and a summary of empirical results.

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

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management and traditional passive management. It appears that – while Smart Beta indeed combines aspects of both active and passive management – in many aspects, Smart Beta is much closer in philosophy to traditional cap-weighted beta than to skill-based or alpha-seeking strategies.

It is clear from this table that Smart Beta strategies in fact resemble traditional cap-weighted beta strategies in many aspects such as transparency, reliance on documented factors and weighting

methodologies, and low fees. This is due to the fact that such strategies are entirely systematic, as is cap-weighting. Smart Beta strategies nevertheless offers three distinct sources of value added, notably i) access to additional rewarded factors beyond the market factor, ii) improved diversification targeted at avoiding exposure to unrewarded risks, and iii) factor risk allocation allowing to exploit information on the risk parameters of a set of factors to construct portfolios that correspond to targeted risk objectives. In the area of Smart Beta, the only true

Exhibit 1: Smart Beta is closer to traditional beta than to "alpha"

Attribute	Discretionary management		Smart Beta indices		Traditional CW Beta	
	Yes/No	Consequences	Yes/No	Consequences	Yes/No	Consequences
Relies on manager skill	✓	Difficulty to identify and retain persistently skilled managers	✗	No manager selection risk	✗	No manager selection risk
Access to risk premia beyond market factor	✓	Manager chooses risk factors	✓	Investor chooses risk factors	✗	No additional premia beyond market
Access to improved diversification to diversify away unrewarded risk (for a given level of factor exposure)	✗	Managers typically follow a "high conviction" strategy with concentrated portfolios	✓	Investor chooses the diversification method	✗	No improved diversification method. Cap-weighting leads to concentration in mega cap stocks
Use of risk-based factor allocation	✓	Manager may choose to include risk-based factor allocation	✓	Investor chooses the factor allocation method based on objectives and constraints	✗	No allocation to premia beyond market
Timing of market/factor returns i.e. tactical bets	✓	Factor timing may help or hurt returns depending on skill and luck	✗	No timing, Smart Beta indices proxy for factors	✗	No timing of factor exposures, cap-weighted indices proxy for the market
Documented source of performance	✗	Bet on the promise of personal skill of the active manager	✓	Academic research and live results documenting the persistence of factor risk premia, diversification, and allocation methods	✓	Access to well-established equity market risk premium
Transparent and systematic	✗	Need to monitor the manager and possible risk-shifting	✓	Explicit choice of risk factors, diversification methods and factor allocation, allows for alignment with investment beliefs	✓	Exposure to single factor and good understanding of risks
Low fees	✗	Performance drag due to high fees	✓	Easily investable at low-cost	✓	Easily investable at low-cost

# 1) The Hiding Game: "Smart Beta Generates Alpha"

source of alpha is factor timing. It is obvious that this source of alpha is not accessible in the framework of systematic Smart Beta strategies. The key difference between Smart Beta and traditional active management is precisely this systematic nature.

Common Smart Beta strategies neither require identifying the rare talent of skilful active managers nor monitoring a manager for potential risk shifting and style drift because they do not rely on alpha and are systematic and transparent.

## A Hiding Game?

We now address a recurrent issue with reporting the performance of Smart Beta strategies. All too often, strategies that simply target a given set of risk factors are evaluated using models that ignore the relevant factors. For example, the founding paper of the so-called Fundamental Indexing by Arnott et al. (2005)<sup>20</sup> assesses the back-tested performance of the proposed strategy. It does not, however, evaluate performance using a multi-factor model. Instead, it is shown that the strategy generates a positive CAPM alpha. However,

the paper does not contain results for standard Fama and French factor exposures or the corresponding multi-factor alpha or any similar measure of alpha which would be adjusted for exposure to standard systematic risk factors. Other authors have criticised this performance evaluation approach and have produced evidence where the same strategy was shown to contain zero alpha with respect to the Fama and French factor model.

This example suggests that conclusions concerning alpha heavily rely on whether appropriate factors are included in the performance evaluation or whether the corresponding factor exposures remain hidden due to the use of a model which omits the relevant factors.

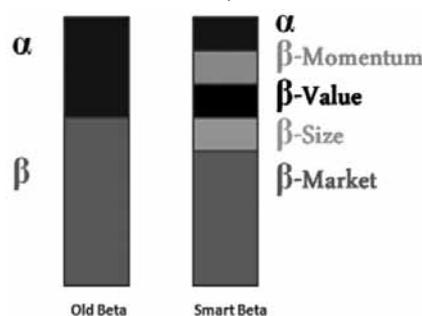
Investors increasingly recognise this difference in portfolio return decomposition under the collective banner "Yesterday's alpha is today's beta". There is a merit in this saying because it highlights the issue in hand – CAPM alpha may come from exposure to additional systematic risk factors and therefore evaporate when the right model is specified. The next exhibit illustrates this point.

Exhibit 2: Published alpha estimates for fundamental weighted composite index

Arnott et al. (2005)	Significantly positive CAPM alpha
Jun & Malkiel (2007) <sup>21</sup>	Zero alpha from Fama French 3 factor model
Blitz & Swinkels (2008) <sup>22</sup>	Insignificant alpha from Fama French 3 factor model

Exhibit 3: Moving from traditional CAPM alpha to multi-factor alpha

This Exhibit illustrates how a simple CAPM view of the world can hide additional risk factors, taken from <http://doubleline.com/archive/wp-content/uploads/2014/11/11-14-Smart-Beta-Revolution.pdf>



20 - Arnott, R.D., J. Hsu and P. Moore. 2005. Fundamental Indexation. *Financial Analysts Journal* 61(2): 83-99.

21 - Jun, D. and B.G. Malkiel. 2007. New Paradigms in Stock Market Indexing. *European Financial Management* 14(1): 118-126.

22 - Blitz, D., and L. Swinkels. 2008 "Fundamental Indexation: An Active Value Strategy in Disguise." Working paper, Robeco and Erasmus University, Rotterdam.

## 1) The Hiding Game: "Smart Beta Generates Alpha"

We provide an illustration of the difference in appraisal that one obtains when using different models for performance evaluation. Here, we evaluate entirely systematic strategies which mechanically tilt to stocks with certain characteristics. We use simple long-only portfolios that represent stock selections of 30% of stocks in the investment universe based on a single variable proxy for valuation, size, investment and profitability.

The following exhibit shows how the regression alpha diminishes when we use multi-factor models instead of the single-factor CAPM. One can observe that using only the market factor results in large alphas, especially for the Value and Low Investment portfolios. Note that these CAPM alphas have nothing to do with unexplained returns or manager skill. They are explained by exposure to a purely mechanical selection of high Book-to-Market stocks (Value), low Market Cap stocks (Size), high Operating Income-to-Assets (Profitability) and low Assets Growth rate stocks (Investment). That stocks with such exposures have higher expected returns is widely known and well documented.

The table below shows the alpha when progressively introducing the Fama French three and five-factor models respectively, which include the market factor augmented by size and valuation for the three factor model and further augmented

by investment and profitability for the five factor model. By changing from a CAPM framework to a multi-factor framework, we uncover the exposure to documented factors. As expected, the alpha drops as the additional risk factors are introduced.

For example, the annualised CAPM alpha is greater than 3% and statistically significant for two of the strategies – Value and Low Investment. When accounting for size and valuation in the three factor model, only two of the strategies have statistically significant and positive alpha estimates with values between roughly 1.5% and 2%. When we consider the five factor model, all alphas are statistically insignificant and close to zero with the highest alpha being about 0.2%. Therefore, as expected, these portfolios do not add any return over what is explained by their factor exposures in the five factor model. This is a clear example of a situation when the "CAPM alpha" is explained away by exposure to well documented factors.

Of course, that these mechanically tilted portfolios simply give exposure to the factors corresponding to the variables used for stock selection seems obvious. However, the results also show that claiming that such portfolios have positive alpha is very easy to do if one focuses on the CAPM regression results without showing the multi-factor results. In practice, the design of Smart Beta strategies may be more complex and the description more ambiguous than for the simple tilted

Exhibit 4: "Where did all the alpha go?"

These tables show annualised alphas of univariate 30% bottom (top) portfolios for different factor models. Portfolios and factors come from Kenneth French's data library. Statistics are annualised. Coefficients significant at the 95% level are highlighted in bold. The analysis is based on monthly data from December 1974 to December 2014 (40 years). Newey-West robust standard errors are employed.

Ann. Alpha	Portfolios based on univariate sorts			
	Value	Smaller Size	High Profitability	Low Investment
	Top 30%	Bottom 30%	Top 30%	Bottom 30%
CAPM	<b>3.32%</b>	1.96%	<b>1.36%</b>	<b>3.16%</b>
Fama French 3 factor model	<b>-1.08%</b>	-0.62%	<b>1.93%</b>	<b>1.45%</b>
Fama French 5 factor model	-0.66%	-0.12%	0.19%	-0.92%

## 1) The Hiding Game: "Smart Beta Generates Alpha"

portfolios used here. But just like in this example, omitting multi-factor alphas from performance reports of Smart Beta strategies could easily obscure the true factor exposures and could falsely suggest that performance is due to some form of manager skill.

### Conclusion

We argue that a careful distinction should be made between the returns due to systematic portfolio construction, and returns due to manager skill. Systematic portfolio construction approaches falling under the Smart Beta umbrella may add value relative to broad-market capitalisation weighted indices due to three distinct components: i) exposure to additional rewarded factors beyond the market factor, ii) improved diversification targeted at avoiding exposures to unrewarded risks, and iii) risk-based multi-factor allocation targeted at delivering explicit risk objectives. None of these approaches can be assimilated with alpha understood as performance attributable to manager-specific skill or attributable to an ability to exploit short-term mispricing in the market or a capacity to time the market or particular categories of stocks. While Smart Beta providers may be tempted to claim that their strategies deliver alpha - in order to justify higher fees for example - the fact that they do not is actually reassuring for users of Smart Beta. Indeed, these three sources of performance can be tapped systematically based on consensual insights and a vast amount of academic evidence, while the search for alpha will continue to be more of an art than a science. Moreover, it appears incoherent to us to criticise active (alpha seeking) managers for their inability to beat the market persistently by timing the market or by picking stocks and at the same time

to suggest that generating alpha can be done by systematic strategies which often rely on backward looking accounting data. Looking for alpha in Smart Beta is not likely to add much value and may instead lead to considerable risk of underperformance.

Manager skill could generate performance over and above that produced by such systematic techniques if it translated in forecasts about future returns on systematic factors of accuracy sufficient to allow for profitable factor-timing<sup>24</sup> or successful bets on idiosyncratic risks e.g. stock picking. Alpha-creation depends on the ability to produce relevant private information, including superior interpretation of public information, so as to make proprietary and possibly discretionary decisions; this does not span very well the most common forms of Smart Beta, which rely on (relatively) transparent and straightforward exploitation of well-documented and consensual sources of returns through (highly) systematic index construction methodologies.

When evaluating systematic strategies, one should be careful to use an appropriate model. Even Smart Beta strategies which tilt to a single consensual factor documented in academic studies and do not optimise diversification should be expected to deliver long-term outperformance over the broad-market capitalisation-weighted index as well as positive CAPM alpha. However, this CAPM alpha is mainly attributable to the fact that the CAPM omits relevant risk factors, including the factor towards which the Smart Beta index tilts. More generally, Smart Beta indices may lead to attractive risk-adjusted performance because of exposure to additional risk factors beyond broad market risk, improved diversification methods, and factor risk allocation. These indices do not aim at generating returns

24 - These forecasts may regard not only factors offering superior long-term rewards, but also other factors that may offer short-lived rewards.

## 1) The Hiding Game: "Smart Beta Generates Alpha"

from tactical bets on factor returns or from bets on non-systematic returns, that is from bets that correspond to the two traditional sources of active management returns or alpha.

While Smart Beta providers may be tempted to claim that their strategies deliver alpha - in order to justify higher fees for example - the fact that they do not is actually reassuring for users of Smart Beta. The existence of positive premia for standard factors such as value, momentum etc. meets a broad consensus and is well documented. The benefits of diversifying away unrewarded risk also constitute a pillar of finance and are taught in every investment management textbook. While not Finance 101 material, the benefits of risk allocation are nevertheless widely documented in academia and draw on a time-tested body of extensive research on risk estimation techniques and dynamic allocation. These three sources of performance can thus be tapped systematically based on consensual insights and a vast amount of academic evidence, while the search for alpha will continue to be more of an art than a science.

## 2) The Monkey Portfolio Claim: "Anything beats cap-weighted market indices"

### Overview of the Claim

Some have argued that the limitations of capitalisation-weighting are so severe that any alternative index construction approach necessarily produces outperformance relative to broad-market cap-weighted indices; the same have gone on to assert that all Smart Beta strategies are essentially the same and add no value beyond what could be achieved by randomly weighting securities. Brightman (2013) states that Smart Beta strategies add value, like Burton Malkiel's (blindfolded) monkey (throwing darts a newspaper's financial pages<sup>26</sup>). The proposition is that the performance of Smart Beta strategies is similar to that of randomly generated non-market cap portfolios also termed "*monkey portfolios*".

The ultimate "proof" of this proposition is the claim made by Arnott et al. (2013)<sup>27</sup> that "*popular strategy indexes, when inverted, produce even better outperformance*". Clearly, if one was to find that inverting a strategy led to adding the same or more value, this would indeed suggest that any alternative scheme beats cap-weighted indices and that "*the investment beliefs upon which many investment strategies are ostensibly based play little or no role in their outperformance*", as the same authors put it.

In the next section, we summarise results from Amenc, Goltz and Lodh (2016)<sup>28</sup> who empirically assess the validity of such claims for a range of Smart Beta strategies.

### Testing Different Strategies

Whether or not a strategy behaves differently from its inverse will depend heavily on the type of strategy that one

tests. For example, if one inverted the weights of an equal-weighted strategy, one would still produce an equal-weighted portfolio, and the fact that the original Smart Beta strategy and its inverse (out) perform identically should not elicit any surprise. For this reason using test portfolios that are explicitly intended to represent some optimisation objective but are constrained to remain at close distance to equal-weighted portfolios, biases study results in favour of the claim that inverse strategies have as much merit as the original strategies. Another key limitation of the studies building the monkey portfolio case is that they are based on first-generation Smart Beta strategies where no explicit choice of factor tilt is taken into account.

Amenc, Goltz and Lodh (2016) use the fundamental-weighted strategy<sup>29</sup> and single factor-tilted portfolios to assess the claim that the performance of Smart Beta strategies remains the same or increases when weights are inverted. Amenc, Goltz and Lodh (2016) avoid creating a bias towards the monkey portfolio conclusion by including a broad set of strategies tilting to different factors and using different weighting schemes that may not be anchored on equal-weighting. To analyse the inversion claim, they construct the inverse or upside-down portfolios for each Smart Beta strategy in a manner similar to that of Arnott et al. (2013). It should, however, be noted that, in addition to inverting the portfolio weights, they also invert the direction of the factor-based stock selection. In the upside-down strategy for value, for example, they select stocks with the lowest value score (i.e. the highest inverse value score) and then tilt the weights towards the stocks with

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

26 - Actually, Malkiel (1973) states that this monkey's portfolio would "do just as well as one carefully selected by experts," but this portfolio does much better than that on average since it not only beats the average active manager but also the market's passive benchmark.

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

28 - Amenc, N., F. Goltz and A. Lodh. 2016. Smart Beta is not Monkey Business. *The Journal of Index Investing* Spring 2016, Vol. 6, No. 4: pp. 12-29

29 - The weight of a stock in the fundamental-weighted strategy is calculated using its composite fundamental score which is the average of four scores for current book-value, trailing five-year cash flow, trailing five-year dividend and trailing five-year sales, respectively. If a score is missing, the composite score is the average score across remaining variables.

## 2) The Monkey Portfolio Claim: "Anything beats cap-weighted market indices"

the lowest value score. The exhibit below shows performance and risk statistics for various test strategies, as well as the corresponding upside-down strategies. We report the results for the fundamental-weighted strategy as well as simple strategies that select the top 50% stocks by factor score and then weight each stock either by its (investability adjusted) factor score or, in the fashion of the ERI Scientific Beta Multi-Strategy indices, according to the average weight of five popular diversification strategies.

The results in the exhibit above are very homogeneous across the different

strategies. While the inverse of the fundamental strategy is associated with slightly higher returns (but slightly lower risk-adjusted returns), the inverted factor-tilted strategies have returns lower than the original strategies (as well as much lower risk-adjusted returns in absolute and relative terms as shown by their Sharpe and information ratios, respectively).

In addition the inverse of score-weighted strategies (which unlike the diversified multi-strategy do not rely on diversification as a source of performance) all underperform the broad cap-weighted index.

*Exhibit 5: Performance and Risk Analysis of Upside-Down Strategies*

*All statistics are annualised and daily total returns from 31 December 1973 to 31 December 2013 are used for the analysis. The CRSP S&P 500 index is used as the cap-weighted benchmark. Yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. Table reproduces the results for "Type 1" upside-down strategies from Exhibit 7 in Amenc, Goltz and Lodh (2016).*

Stock Selection	Weighting Scheme	Ann Returns	Ann Volatility	Sharpe Ratio	Ann Rel. Returns	Ann Trk. Error	Information Ratio
All Stocks	Fundamental Wtd	12.51%	16.84%	0.43	1.56%	3.58%	0.44
All Stocks	Upside-down	12.62%	17.21%	0.42	1.67%	4.08%	0.41
Mid Cap	Div Multi-Strategy	15.67%	16.69%	0.62	4.72%	6.65%	0.71
Large Cap	Upside-down	12.11%	18.10%	0.38	1.16%	3.45%	0.34
High Momentum	Div Multi-Strategy	14.57%	16.26%	0.57	3.62%	4.83%	0.75
Low Momentum	Upside-down	12.53%	19.68%	0.37	1.58%	7.99%	0.20
Low Volatility	Div Multi-Strategy	13.90%	14.34%	0.60	2.95%	6.13%	0.48
High Volatility	Upside-down	13.06%	21.31%	0.36	2.11%	7.77%	0.27
Value	Div Multi-Strategy	15.70%	16.51%	0.63	4.75%	5.74%	0.83
Growth	Upside-down	11.61%	18.47%	0.34	0.66%	4.82%	0.14
Low Investment	Div Multi-Strategy	15.18%	15.50%	0.64	4.23%	5.61%	0.75
High Investment	Upside-down	12.00%	19.40%	0.34	1.05%	5.58%	0.19
High Profitability	Div Multi-Strategy	14.31%	16.13%	0.56	3.36%	4.48%	0.75
Low Profitability	Upside-down	13.02%	19.12%	0.40	2.07%	6.91%	0.30
Mid Cap	Mid Cap Score Wtd	15.40%	18.34%	0.55	4.45%	7.40%	0.60
Large Cap	Upside-down	9.91%	17.80%	0.26	-1.04%	2.72%	-0.38
High Momentum	Momentum Score Wtd	12.91%	18.35%	0.41	1.96%	5.69%	0.34
Low Momentum	Upside-down	8.10%	21.15%	0.13	-2.85%	9.04%	-0.32
Low Volatility	Low Volatility Score Wtd	11.49%	14.75%	0.42	0.54%	5.91%	0.09
High Volatility	Upside-down	9.06%	26.07%	0.14	-1.89%	12.42%	-0.15
Value	Value Score Wtd	14.89%	18.52%	0.52	3.94%	5.94%	0.66
Growth	Upside-down	8.88%	18.06%	0.20	-2.07%	4.10%	-0.51
Low Investment	Low Inv Score Wtd	13.26%	16.35%	0.49	2.31%	4.42%	0.52
High Investment	Upside-down	9.15%	19.67%	0.19	-1.80%	4.79%	-0.38
High Profitability	High Prof Score Wtd	11.52%	17.40%	0.36	0.57%	4.66%	0.12
Low Profitability	Upside-down	10.37%	20.02%	0.25	-0.58%	7.43%	-0.08

## 2) The Monkey Portfolio Claim: "Anything beats cap-weighted market indices"

These results are consistent with the original (long-only) factor-based strategies actually delivering the outperformance that has been documented in academic studies as being associated with the right tilts along their respective factor dimensions. Tilting in the opposite directions, the inverse strategies underperform in a manner consistent with the academic literature on factor investing (in the long/short context of the reference academic studies, these selections would be shorted to improve portfolio performance).

### Conclusion

Smart Beta strategies are not created equal and both factor exposures and diversification approaches matter. Inverting popular Smart Beta strategies need not improve performance and could even result in under-performance. As shown in Amenc, Goltz and Lodh (2016), inverting Smart Beta strategies tilted towards factors associated with long-term over-performance, that is the very strategies that have been extremely popular for a number of years and continue to be favoured by investors, produces long-term performance and risk-adjusted performance that are significantly lower than what the original strategies deliver. Furthermore, when the original strategies do not tap diversification as a source of performance but instead concentrate portfolios through factor score weighting, the inverted strategies also underperform the broad capitalisation-weighted market index. These findings contradict the monkey portfolio claim that anything will beat the cap-weighted index and proves wrong the assertion that inverting Smart Beta strategies will improve performance. Targeting factor tilts that are negatively rewarded (such as large-cap, growth, low momentum,

high volatility, low profitability or high investment) should not be expected to lead to outperformance in the long-term. Smart Beta strategies are not monkey portfolios and investors cannot rely on the belief that any alternative weighting will deterministically improve performance and choose Smart Beta strategies in the manner of Malkiel's monkey. Investing in Smart Beta strategies requires due diligence covering the factor tilts and diversification mechanisms employed if an investor is to select a strategy that corresponds to its investment objectives and beliefs.

Proponents of monkey portfolio arguments are perhaps just creating a smokescreen to hide poor live performance of the products they promote but do a disservice to investors who are interested in understanding the risks and the robustness (or lack thereof) of Smart Beta performance across different types of strategies. Claiming that all Smart Beta strategies are identical can be seen as an attempt to discourage thorough analysis of alternative solutions in terms of robustness and risks.

### 3) The Value and Size Myth: "All Smart Beta performance comes from value and small cap exposure"

#### Overview of the Claim

Some argue that once one deviates from selecting and weighting stocks on the basis of their market value, as is done in capitalisation-weighted indices, one necessarily introduces positive value and size factor exposures. For example Arnott et al. (2013)<sup>30</sup> state that any Smart Beta strategy "necessarily results in value and size tilts, regardless of the weighting method chosen", while Chow et al. (2011)<sup>31</sup> claim that Smart Beta strategies "outperform because of the positive value and size loadings" given that "none of these strategies are different from naive equal-weighting".

#### Testing Smart Beta Strategies

To test the assertion that all Smart Beta strategies have the same factor exposures Amenc, Goltz and Lodh (2016) measure the factor exposures of commonly-used fundamental and explicitly factor-based Smart Beta strategies using a multi-factor

model accounting for the most consensual equity factors. Their regressions rely on a 7-factor model which uses the High Profitability and Low Investment factors introduced in Fama and French (2015)<sup>32</sup> and the Betting-Against-Beta (BAB) factor put forward in Frazzini and Pedersen (2014)<sup>33</sup> in addition to the four factors of the Carhart (1997)<sup>34</sup> model (which added the Momentum factor to the Market, Value and Size factors of the seminal Fama and French (1993) model). The resulting regression coefficients are reported in the exhibit below.

If the claims hold for the test portfolios, regression coefficients for the Size and Value factors should be significantly positive for all strategies and regression coefficients for all other factors should be insignificant (these being long-only portfolios, the significance of the market factor is not at doubt). Finally, all strategies should exhibit the factor loadings, or the same coefficient signs as equal-weighting.

Exhibit 6: Seven-Factor Regression – From Amenc, Goltz and Lodh (2016)

The Market factor is the excess returns of the CRSP S&P 500 index over risk-free rate. The yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. The Size, Value, Momentum, High Profitability, and Low Investment factors are obtained from the Kenneth French data library. The Betting-Against-Beta (BAB) factor is obtained from the Andrea Frazzini data library. The Newey-West (1987) estimator is used to correct for autocorrelation. Daily total returns from 31 December 1973 to 31 December 2013 are used for the analysis. Regression coefficients that have p-values less than 5% are highlighted in bold. Alphas are annualised.

Weighting Scheme	Stock Selection	Ann Alpha	Market Beta	SMB Beta	HML Beta	MOM Beta	BAB Beta	Prof. Beta	Invest. Beta	R-Squared
Cap Weighting (Benchmark)	All Stocks	-	<b>1.00</b>	-	-	-	-	-	-	100.0%
Fundamentals-Based	All Stocks	-0.48%	<b>1.00</b>	<b>0.02</b>	<b>0.26</b>	<b>-0.04</b>	<b>0.01</b>	<b>0.04</b>	<b>0.13</b>	98.3%
Equal-Weighting	All Stocks	0.94%	<b>1.03</b>	<b>0.27</b>	<b>0.18</b>	<b>-0.10</b>	0.02	0.00	<b>0.09</b>	96.5%

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

31 - Chow, T., J. Hsu, V. Kalesnik and B. Little. 2011. A Survey of Alternative Equity Index Strategies. *Financial Analysts Journal* 67(5): 37-57.

32 - Fama, E.F. and K.R. French. 2015. A Five-Factor Asset Pricing Model. *Journal of Financial Economics* 116(1): 1-22.

33 - Rank-weighted portfolios that are long the 50% low market beta stocks and short the 50% high market beta stocks are constructed. Betas are estimated using the shrinkage method of Vasicek (1973) for long and short legs separately. Both long and short portfolios are rescaled to have a beta of one at portfolio formation. See Frazzini, A. and L. Pedersen. 2014. Betting Against Beta. *Journal of Financial Economics* 111(1): 1-25.

34 - Carhart, M. 1997. On Persistence in Mutual Fund Performance. *Journal of Finance* 52(1): 57-82.

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Diversified Multi-Strategy	Mid Cap	0.54%	1.01	0.42	0.26	-0.03	0.05	0.03	0.17	91.8%
	Momentum	-0.04%	0.98	0.20	0.09	0.17	0.06	0.01	0.08	95.2%
	Low Vol	-0.78%	0.88	0.10	0.14	-0.02	0.10	0.19	0.27	92.8%
	Value	0.60%	1.00	0.24	0.40	0.02	0.05	-0.02	0.08	94.7%
	Low Invest.	-0.19%	0.96	0.24	0.17	0.02	0.07	0.04	0.32	94.4%
	High Prof.	1.68%	0.95	0.23	-0.09	-0.03	0.04	0.08	0.17	94.9%
Score x Market Cap Weighting	Mid Cap	1.84%	1.06	0.45	0.26	-0.19	0.01	-0.01	0.18	92.0%
	Momentum	0.12%	1.02	0.03	0.00	0.40	-0.02	-0.10	-0.13	96.8%
	Low Vol	-2.36%	0.87	-0.11	-0.03	0.02	0.09	0.27	0.37	94.5%
	Value	2.34%	1.05	0.07	0.57	-0.01	-0.03	-0.19	-0.14	95.7%
	Low Invest.	-1.09%	0.99	0.06	0.00	0.03	0.03	0.00	0.52	96.8%
	High Prof.	1.56%	0.94	-0.02	-0.33	0.03	-0.01	0.19	0.01	96.0%

We report the results for the fundamental-weighted strategy,<sup>35</sup> the equal-weighted strategy as well as simple strategies that select the top 50% stocks by factor score and then weight each stock either by its (investability adjusted) factor score or, in the fashion of the ERI Scientific Beta Multi-Strategy indices, according to the average weight of five popular diversification strategies. Inspection of the results in the exhibit below shows that none of these conditions is satisfied by the results.

#### Value and Size tilts are common but not ubiquitous

The exhibit above shows that, even though most strategies do have (statistically significant) positive exposure to small-cap and value, some strategies do have negative exposure, sometimes to both of these factors. This is notably the case of the Low Volatility and High Profitability score-weighted strategies. Despite deviating from the cap-weighted index, these strategies do not lead to a Value and Small Cap tilt, but actually to a Growth and Large Cap tilt. Therefore, it is not valid to claim that all Smart Beta strategies have positive Value and Size loadings, even though many strategies do. Moreover, given the negative exposure of some strategies to

Value and Small Cap, it would not make sense to claim that the outperformance of these portfolios is (fully) explained by their Size and Value exposures as the latter negatively impact performance. It is probably fair to say that a majority of investors are aware that there are factors beyond those used in the Fama and French (1993) model and that it is possible to control factor exposures in Smart Beta strategies, as was formalised by Amenc et al. as early as 2012<sup>36</sup>.

#### There are many more factors and they play a major role

The results also show that most strategies have significant exposures to factors other than Value and Small Cap. This is not surprising given the ample evidence on the importance of these extra factors, and the fact that some indices in the set of strategies explicitly seek exposure to such factors. For example, the Low Investment strategies lead to investment factor loadings of 0.32 and 0.52, with diversified and score weighting, respectively. The Momentum strategies exhibit momentum beta of 0.17 and 0.40, respectively. For the score-weighted strategies, the largest significant factor exposure measured by the regression typically corresponds to the factor that is explicitly targeted while

35 - As previously mentioned the weight of a stock in the fundamental-weighted strategy is the simple average of four scores for current book-value, trailing five-year cash flow, trailing five-year dividend and trailing five-year sales.

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

### 3) The Value and Size Myth: "All Smart Beta performance comes from value and small cap exposure"

the exposures to the Small Cap and Value factors, when statistically significant and of the right sign, are of a second-order. Naturally, diversified strategies come with statistically and economically significant exposure to the Small Cap factor since deconcentration away from capitalisation-weighting mechanically reduces exposure to the largest capitalisation stocks. As a result these strategies exhibit statistically and economically significant positive exposure to the Small Cap factor that sometimes is as high as or higher than the exposure to the factor that is explicitly targeted.<sup>37</sup> Even with diversified factor-tilted strategies, the cumulated Small Cap and Value exposures do not dominate the cumulated exposure to the Momentum, BAB, Profitability and Investment factors. While these results are admittedly unsurprising, they invalidate the monkey portfolio proponents' claim that Smart Beta strategies do nothing but tilt towards Small Cap and Value.

Amenc, Goltz and Lodh (2016)<sup>38</sup> go further and take into account the risk and return characteristics of factors to analyse the contribution of the different factors to the returns and risks of Smart Beta strategies; they find that factors other than Size and Valuation play a major role. They also document that many strategies present a considerable portion of unexplained performance which suggests that the portfolio construction of these indices captures effects that cannot be explained fully by the relevant factors. Possible explanations of this unexplained part of performance are that the improved diversification scheme allows value to be added beyond the explicit factor tilts, or that yet other additional factors, which are omitted from the factor model, are at

work.

#### **Factor exposures are different than those of equal-weighted indices**

The results in the previous exhibit also provide evidence that most of these strategies are opposed to equal-weighting in terms of momentum exposure. Moreover, the equal-weighted strategy does not have significant exposures to the BAB factor and the Profitability factor. On the contrary, many of the factor-tilted strategies have significant exposure to the BAB and Profitability factor. For strategies offering explicit tilts, the cumulated Small Cap and Value exposures do not dominate the cumulated exposure to the Momentum, BAB, Profitability and Investment factors (except for strategies targeting Small Cap and Value naturally). The opposite is true for equal-weighting. In this sense, the factor-tilted indices offer investment opportunities that cannot be captured by an equal-weighted index.

#### **Conclusion**

The factor exposures in the results presented above directly invalidate the claim that all Smart Beta strategies are exposed to Small Size and Value and that these factor exposures explain away their outperformance. Instead, they document exposure to multiple factors beyond (Market,) Value and Size and find that Smart Beta strategies can be dominated by and derive the bulk of their outperformance from these additional factor exposures. This finding may not be surprising, and is fully consistent with the academic literature, which has documented the importance of various equity risk factors beyond Value and Small Cap (Leote de Carvalho, Lu and Moulin (2012)<sup>39</sup>; Clarke, de Silva and

37 - Over the long-term, deconcentration has also meant increasing the Value exposure as the largest caps have tended to be Growth stocks. Hence diversified factor-tilted strategies typically have positive exposure to the Value factor although it is of a second order - note that the strategy tilting towards High Profitability has a statistically significant negative exposure to Value indicating that the by-product effect of diversification (mid caps have tended to be Value stocks over the period) is more than offset by factor-tilting (highly profitable companies have tended to be Growth stocks over the period).

38 - Cited above

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

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

### 3) The Value and Size Myth: "All Smart Beta performance comes from value and small cap exposure"

Thorley (2013)<sup>40</sup>; Asness, Moskowitz and Pedersen (2013)<sup>41</sup>; Asness, Frazzini and Pedersen, (2013)<sup>42</sup>).

While alternative weighting schemes, by deviating from standard cap-weighted indices, indeed lead to introduce implicit factor exposures (notably Small Size), using alternative weighting schemes without providing any option to also target explicitly at factor exposures corresponds to a first generation Smart Beta approach, also referred to as Smart Beta 1.0. Such approaches are rather limited as they do not allow for an explicit choice of risk factor exposures or control of such exposures but instead rely on deconcentration with respect to cap-weighted indices. This naturally leads to avoiding the Large Cap bias of cap-weighted indices and their typical Growth exposure over the long-term. However, this does not allow for controlling the deviations from cap-weighting and thus leads to implicit factor exposures and potentially to other unmanaged and undocumented risks (e.g. sector exposures). It has been documented for example that fundamentally-weighted indices, which are instances of Smart Beta 1.0 strategies, lead to pronounced sector biases, for example to an overweight of financial stocks and an underweight of technology stocks in the period prior to the Global Financial Crisis, which may become a main driver of short-term performance without necessarily providing an expected long-term reward (see Amenc et al. (2012a<sup>43</sup>)). The Smart Beta 2.0 approach introduced in Amenc et al. (2012b<sup>44</sup>) allows exposures to be controlled by constructing Smart Beta strategies in two independent steps: the selection of constituents and the choice of a diversification-based weighting scheme. Within this framework, it is straightforward to correct the implicit

tilts of weighting schemes through the prior selection of stocks with appropriate characteristics. This also allows for the design of indices that combine the benefits of explicit tilts towards desired factors and the improvement in risk-return characteristics brought by the application of diversification-based weighting schemes. This flexible approach allows for explicit control of factor exposures and invalidates the claim that all Smart Beta strategies are necessarily tilted towards Small Cap and Value.

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

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

43 - Amenc, N., F. Goltz and A. Lodh. 2012a. Choose Your Betas: Benchmarking Alternative Equity Index Strategies. *Journal of Portfolio Management* 39(1): 88-111.

44 - Amenc, N., F. Goltz and S. Ye. 2012b. Seeing Through the Smoke Screen of Fundamental Indexers: What are the Issues with Alternative Equity Index Strategies? EDHEC-Risk Institute Working Paper (July).

## 4) The Rebalancing Fantasy: "Smart Beta outperforms because it trades against mean reversion"

### Overview of the Claim

Smart Beta strategies differ from broad-market capitalisation-weighted benchmarks (hereafter market indices) in many ways. A straightforward difference is rebalancing. Market indices essentially represent buy-and-hold strategies, as target security weights are directly proportional to the market capitalisations of securities, changes in index weights caused by changing security prices exactly correspond to the changes required to maintain the indices in line with their objectives; hence these indices rebalance naturally to target weights without creating any turnover.<sup>45</sup> By contrast, Smart Beta strategies determine target weights which by definition are different from the weights applied to strategy constituents in market indices. Indeed, these alternative weights are intended to establish the desired factor exposures of the strategies and/or implement their diversification approaches. Price fluctuations cause constituent weights to drift away from target weights (as do changes in the other characteristics of eligible securities that affect factor-tilting and diversification weighting). To bring back Smart Beta strategy portfolios in line with strategy objectives, constituents and weights are reset at regular intervals, which causes significant turnover.

As Smart Beta strategies are rebalanced partly to oppose the drift in constituent prices that is caused by the ebb and flow of markets, some have argued that the performance of these strategies relative to market indices is explained away by the benefits of rebalancing against markets, which are assumed to be mean-reverting. This became known as the rebalancing effect. For example, some providers identify it as a key source of Smart Beta performance:<sup>46</sup>

"By rebalancing periodically, you keep breaking the relationship between price and weight and you trade against mean reversion. We believe this is the biggest reason why most smart-beta strategies outperform." Others go as far as saying that this alleged effect is the only source of outperformance in the long term: "... the long-term performance of many Smart Beta strategies ... can be attributed to this [rebalancing] phenomenon."<sup>47</sup> or at any horizon: "It is the rebalancing that provides the outperformance [of Smart Beta strategies]"<sup>48</sup>.

### Rebalancing with fundamentals-based strategies

To highlight the sometimes confusing nature of rebalancing claims, it is interesting to look at three effects which are documented in the literature, and indeed often assimilated with rebalancing effects of an early form of Smart Beta strategy, known as fundamental equity indexation. In a nutshell, we show that, while several well-documented effects exist, there is little conceptual reason to think that these effects could be captured with the type of weighting schemes employed by fundamental indices.

There are several findings in the academic literature that are frequently cited to support the claim of a rebalancing effect. A first reference is to the literature on contrarian strategies which leads to lower (higher) weights in stocks that have increased (decreased) in price. Adopting a contrarian behaviour should lead to performance benefits if it allows the capture of documented "return reversal" effects (Lakonishok et al. (1994)<sup>49</sup> find that Glamour stocks under-perform Value stocks as investors slowly realise that they

45 - The limited turnover recorded by capitalisation-weighted indices is a result of changes in the universe of eligible securities, changes in the free float and foreign ownership restrictions of index constituents and corporate actions.

46 - Steward, M. 2014: Smart Beta: Smart investing or smart trading?, IPE Report, March 2014

47 - Yashenchak, R. and Valerie Azuelos, 2014. Volatility and Rebalancing as a Source of Return. Intech Publication

48 - The maths professor's smart-alpha sums add up. *Financial Times*. January 11, 2015

49 - Lakonishok, J., Shleifer, A. and Vishny, R. W. 1994. Contrarian Investment, Extrapolation, and Risk. *Journal of Finance* 49(5): 1541-1578.

## 4) The Rebalancing Fantasy: "Smart Beta outperforms because it trades against mean reversion"

have extrapolated the recent growth in sales, earnings and cash flow of Glamour stocks too far in the future). Another aspect of rebalancing is that even when security prices follow a random walk (i.e. they experience neither mean-reversion nor momentum), strategies that rebalance to fixed weights strategy grow more rapidly in portfolio value than buy-and-hold strategies based on the same securities (Dempster, Evstigneev and Schenk-Hoppe (2007)<sup>50</sup>) - the higher the difference in volatility between the two types of strategies, the larger this theoretical effect.<sup>51</sup> Yet another support for the rebalancing argument is the reference to mean reverting returns at the market level. It is in fact well known that stock-market returns are mean reverting in the long-term. For example, Poterba and Summers (1988)<sup>52</sup> provide international evidence of the prevalence of mean reversion in long-term returns at the stock-market level.

A common notion among those that consider that rebalancing as a key source of value in fundamental indexing strategies is that rebalancing profits can be extracted by low turnover strategies that update weights at low frequency on the basis of slow moving accounting variables which ignore any price information. As sometimes voiced by practitioners, a key idea behind such low frequency fundamentals-based weighting strategies is that stock prices supposedly revert to so-called fundamental values. However, the alleged reversion to fundamental values is not something that can be directly linked to the three different strands of literature cited above.

Firstly, the 'contrarian effect' relies on market price information, whereas proponents of fundamental indexing regard market prices as "too noisy relative to fundamentals"<sup>53</sup> and employ only fundamental information to weight stocks.<sup>54</sup> Secondly, rebalancing to ad-hoc fixed weights to improve portfolio growth over times is different from rebalancing to changing weights determined by fundamental data. Moreover, growth-rate strategies are typically implemented at the high frequency to make the most of this mechanical rebalancing effect. Thirdly, the well-documented 'mean reversion' in stock returns refers to (a time series effect at) the asset class level, rather than to (a cross sectional effect at) the individual stock level. It is thus unclear how an alternatively weighted equity indexing strategy where constituent weights are determined by stock-level accounting measures can benefit from such an aggregate asset class effect. It can also be noted that studies of aggregate market mean reversion take into account prices, often through the use of price-to-dividend ratios, and thus a strategy that would really be divorced from prices would not be likely to capture such an effect.

Overall, it appears that these strategies that claim to have the rebalancing effect as a key driver of their performance are not suitably designed to capture any of the documented effects often assimilated with rebalancing.

In order to provide some perspective on rebalancing effects in Smart Beta strategies, we further review the literature below and then report our own empirical tests.

50 - Dempster, M.A., I.V. Evstigneev and K.R. Schenk-Hoppé. 2007. Volatility-Induced Financial Growth. *Quantitative Finance* 7(2): 151-160.

51 - This has inspired "volatility pumping" strategies that magnify the effect by using high volatility assets.

52 - Poterba, J.M. and L.H. Summers. 1988. Mean Reversion in Stock Prices: Evidence and Implications. *Journal of Financial Economics* 22(1): 27-59.

53 - Arnott, R. D., Hsu, J., and Moore, P. 2005. Fundamental Indexation. *Financial Analysts Journal*. Volume 61, Number 2, 83-99.

54 - To the extent that Fundamental Indexing strategies were implicit Value strategies, as explained by Asness (2006) or Kaplan (2008)\* and quantified by Amenc et al. (2008)\*\*, they could benefit from the reversal effect. However, their promoters insist that Fundamental Indices should not be equated with Value indices and that their Value bias is dynamic and a by-product of their weighting. Estrada (2008)\*\*\* and Amenc et al. (2008) document that Fundamental Indexing strategies are dominated by traditional Value strategies.

\* Kaplan, P.D. 2008. Why Fundamental Indexation Might-or Might Not-Work. *Financial Analysts Journal* 64(1): 32-39.

\*\* Amenc, N., F. Goltz and V. Le Sourd. 2008. A Comparison of Fundamentally Weighted Indices: Overview and Performance Analysis. EDHEC-Risk Institute Publication (March).

\*\*\* Estrada, J. 2008. Fundamental Indexation and International Diversification. *Journal of Portfolio Management* 34(3): 93-109.

## 4) The Rebalancing Fantasy: "Smart Beta outperforms because it trades against mean reversion"

### Debate on the rebalancing effect

That any Smart Beta strategy would outperform automatically because of a "rebalancing return" is inconsistent with the academic literature. Empirical research has shown that rebalancing effects are highly dependent on the time horizon. There is ample evidence not only of return reversal effects, but also of return continuation or momentum effects (at the market level in Poterba and Summers (1988) and as the stock-level in Jegadeesh and Titman (1993))<sup>55</sup>. More recently, Plyakha, Uppal and Vilkov (2014)<sup>56</sup> find that equal-weighted portfolios can benefit from short-term reversal effect but only if the rebalancing frequency is much higher than typical Smart Beta index rebalancing frequencies (this is consistent with the evidence in Jegadeesh and Titman (1993)). It is also worth noting that the popular asset pricing models introduced by Fama and French (1993<sup>57</sup>, 2015<sup>58</sup>) do not include any rebalancing factor and that the extension introduced by Carhart (1997)<sup>59</sup> includes a short-term Momentum factor that does the opposite of a contrarian strategy.

A recent paper by Cuthbertson, Hayley, Motson and Nitzsche (2015)<sup>60</sup> notes that while the theoretical literature concludes that rebalancing increases the rate of portfolio growth, the empirical evidence is unresponsive. The paper underlines that, in the absence of mean reversion in relative asset prices, the greater expected growth of rebalanced strategies is solely due to their lower volatilities (and not to the alleged profitability of rebalancing trades). It distinguishes between "rebalancing returns" that would be "specific to the act of rebalancing" and "diversification returns" available to rebalanced and non-

rebalanced portfolios alike and finds that the difference between the expected growth rates of rebalanced and un-rebalanced portfolios of assets that are independently and identically distributed is entirely explained by portfolio diversification. The paper warns against misleading claims about the benefits of rebalancing driving investors into concentrated strategies with high turnover and concludes that "Investors would be better advised to seek to minimize volatility drag by diversifying effectively and to rebalance no more than is necessary to keep their portfolio compositions adequately close to their target allocations."

Indeed, it is intuitive that a buy-and-hold portfolio which is never rebalanced, can lead to high concentration in assets that perform well relative to the other assets in the portfolio. To maintain a constant level of deconcentration in a portfolio that aims at naive diversification, rebalancing to fixed (equal) weights is required. If a portfolio is constructed using risk estimates to aim for scientific diversification, rebalancing is an opportunity to consider updated information on the (risk) parameters of securities and target new optimal weights. In the presence of transaction costs, there is a trade-off between the benefits of resetting weights to maintain the strategy and the costs associated with turnover.

The literature on the effects of rebalancing can also be slightly confusing. For example, the terms "diversification return", "volatility return" and "rebalancing premium" are sometimes used interchangeably by authors and the whole concept of studying rebalancing as a source of added value is frequently overshadowed by disagreements between what exactly should be measured.

55 - Jegadeesh, N. and S. Titman. 1993. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance* 48(1): 65-91.

56 - Plyakha, Y., R. Uppal and G. Vilkov. 2014. Equal or Value Weighting? Implications for asset-Pricing Tests. SSRN Working Paper. Available at: [http://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=1787045](http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1787045).

57 - Fama, E. F. and K. R. French. 1993. Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics* 33(1): 3-56.

58 - Fama, E. F. and K. R. French. 2015a. A Five-Factor Asset Pricing Model. *Journal of Financial Economics* 116(1): 1-22.

59 - Carhart, M.M., 1997. On Persistence in Mutual Fund Performance. *The Journal of Finance* 52(1): 57-82.

60 - Cuthbertson, K., S. Hayley, N. Motson and D. Nitzsche, 2015. Diversification Returns, Rebalancing Returns and Volatility Pumping. SSRN Working Paper. Available at: [http://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=2311240](http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2311240).

## 4) The Rebalancing Fantasy: "Smart Beta outperforms because it trades against mean reversion"

For example, Erb and Harvey (2005)<sup>61</sup> criticised the results of an earlier version of the study by Gorton and Rouwenhorst (2006)<sup>62</sup> that examined the performance of (implicitly rebalanced) portfolios of commodities. Erb and Harvey claimed that this performance did not come from the commodity asset class itself (as they found the average return of the average commodity futures contract was not statistically different from zero), but was a result of the rebalancing methodology. They compared the performance of a buy-and-hold (initially equal-weighted) portfolio of commodities with that of a periodically rebalanced equal-weighted portfolio and found higher returns for the rebalanced portfolio. They computed the "diversification return" as the difference between the portfolio return and the weighted average return of the constituents asserted that it was due both to variance reduction and rebalancing. In a response, Gorton and Rouwenhorst (2006)<sup>63</sup> underline that it is a mathematical fact that geometric average returns are lower than arithmetic average returns (by about half the variance of returns) and because portfolios diversify some of the risk in individual assets, portfolios will on average outperform their constituents in terms of geometric averages. Thus there is not much that can be understood by studying the difference between a portfolio return and the weighted return of its constituents. Gorton and Rouwenhorst (2006) further provide updated results for different rebalancing periods of their commodity portfolios and argue that rebalancing is an embedded trading strategy which may or may not positively affect performance, depending on the realised price paths of

the assets (assuming these do not follow a random walk).

Recently, in light of the measuring confusion, Hallerbach (2014)<sup>64</sup> proposed to go back to the basics and measure the rebalancing return as the difference between the geometric mean returns of rebalanced and buy-and-hold strategies and argued it should be broken down into two separate effects<sup>65</sup> – the volatility effect (arising from randomness of asset returns) and the dispersion discount (due to differences in asset returns)<sup>66</sup>. Similarly, Qian (2014)<sup>67</sup> follows this logic and argues that since both effects are non-negative for long-only portfolios, rebalancing alpha will depend on the relative magnitude of both effects. In other words, whether the rebalanced portfolio will outperform the buy and hold portfolio or underperform it will depend on the behaviour of the component assets (in the cross-section and across time).

A strong argument against the rebalancing effect as a sole return driver is to consider the returns of portfolios which tilt to different directions for the same factor and follow the same rebalancing schedule. This argument is put forth by Blitz (2015)<sup>68</sup>. Factor-tilted portfolios in academic studies are based on sorts of stocks on a given characteristic. For example, a Value-tilted portfolio may be constructed as the top quintile of stocks sorted by the Book-to-Market ratio. The opposite tilt – to growth) can be constructed as the corresponding bottom decile. It is then clear that both the value-tilted portfolio and the growth-tilted portfolio involve similar amounts of rebalancing. However, it is a well established

61 – Erb, C.B. and C.R. Harvey. 2005. The Strategic and Tactical Value of Commodity Futures. *Financial Analysts Journal* 62(2): 69-97.

62 – Gorton, G. and K.G. Rouwenhorst. 2006. Facts and Fantasies about Commodity Futures. *Financial Analysts Journal* 62(2): 47-68.

63 – Gorton, G. and K.G. Rouwenhorst. 2006. A Note on Erb and Harvey (2005). Yale ICF Working Paper No. 06-02.

64 – Hallerbach, W.G., 2014. Disentangling Rebalancing Return. *Journal of Asset Management* 15(5): 301-316.

65 – Rebalancing return = Volatility return – Dispersion discount

66 – Volatility return = Return of rebalanced portfolio – Weighted return of the constituents; Dispersion discount = Return of buy and hold portfolio – Weighted return of the constituents

67 – Qian, E. E. 2014. A Mathematical and Empirical Analysis of Rebalancing. *Journal of Portfolio Management* (Forthcoming). Available at SSRN: <http://ssrn.com/abstract=2543705>.

68 – Blitz, D. 2015. Is Rebalancing the Source of Factor Premiums? *The Journal of Portfolio Management*: 41(4): 4-7.

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empirical finding that the growth tilt produces underperformance while the value tilt produces outperformance. Blitz (2015) argues that, since factor premiums are "quite symmetric on the positive and negative side" and both outperforming and underperforming factor-tilted portfolios have similar rebalancing characteristics, rebalancing cannot be the driver of performance.

The previous argument also provides a link between the discussion on rebalancing and the discussion about upside-down strategies that we presented in this document in Misconception number 2 (The Monkey Portfolio Claim). That section reviews the results from Amenc, Goltz and Lodh (2016), who study the performance of Smart Beta strategies and their inverses. The originals and the inverses that they construct experienced different performance. Many of the mirror-image portfolios, notably those using score-weighting, underperformed the cap-weighted index as opposed to the original factor-tilted strategies exposed to the rewarded factors that outperformed the benchmark. However, all the factor-tilted strategies<sup>69</sup> in their study are rebalanced at the same frequency – quarterly. This means that the portfolios tilted to the rewarded factors as well as their corresponding inverses, produce different risk-adjusted performance despite sharing the same rebalancing patterns which points to the conclusion that rebalancing cannot explain their performance. This interpretation is perfectly in line with Blitz's argument.

When trying to assess the claim that Smart Beta performances are driven by the rebalancing effect, there are in fact several questions that one can assess. Below, we provide three different empirical tests to analyse this issue. First, we will assess across

a range of test assets whether rebalancing generates extra performance. If it did, this would not automatically mean that commonly used Smart Beta strategies draw on this source of performance. But if it did not, this would strongly undermine the claim that Smart Beta strategies benefit from this effect. Second, we will look at a simple strategy – equal weighting – to check if one benefits from rebalancing more often and also analyse the factor exposure of strategies rebalanced at different frequencies. If indeed rebalancing is the main driver of returns, rebalancing a strategy more frequently should yield benefits. Thirdly, we look directly at common factor portfolios and test whether their performance is related to proxies for rebalancing returns. We now look at each assessment in turn.

### Empirical Test I: Is rebalancing a mechanical driver of performance?

We follow the recent literature and measure the rebalancing effect as the difference between the performances of periodically rebalanced portfolios (for simplicity, the weighting scheme applied is that of equal weights) and the buy-and-hold portfolio, initially also equal weighted. The literature review already points out that from a theoretical stand point, it is not correct to assume that the rebalanced portfolio will automatically outperform the buy-and-hold portfolio.

To assess this problem empirically and avoid the problem of survivorship bias on the individual stock level, we use sorted portfolios from Kenneth French's data library as the underlying portfolio building blocks. The exhibit below presents the results from using the available portfolios based on univariate sorting and arranged

69 – Apart from factor-tilted strategies, Amenc, Goltz and Lodh (2016) also construct fundamental weighted strategies based on all the stocks. These strategies are rebalanced annually.

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Exhibit 7: Comparison of Sharpe ratios between rebalanced and buy and hold portfolios for multiple time periods

The table shows the Sharpe ratios of portfolios formed by periodically rebalancing the underlying constituents. The underlying constituents are portfolios themselves, based on monthly data of univariate stock selection deciles officially published in Kenneth French's data library. Each column thus works with 10 underlying portfolios and the sorting variable is indicated in the column headers. For details of calculations of the individual portfolios and the variable definitions, consult Kenneth French's website at [http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data\\_library.html](http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

USA portfolios		Underlying constituents – 10 portfolios, sorted into deciles by variables in the column headers												
Period	Rebalancing Frequency	Momentum	Accruals	Book-to-Market	Beta	Cash Flow-to-Price	Dividend Yield	Earnings-to-Price	Investments	Market Equity	Net Share Issuance	Operating Profitability	Residual Variance	Variance
40 years (1976 - 2015)	Monthly	0.40	0.45	0.55	0.47	0.54	0.52	0.55	0.51	0.49	0.40	0.42	0.40	0.41
	Quarterly	0.41	0.45	0.55	0.47	0.54	0.52	0.55	0.52	0.49	0.40	0.42	0.40	0.41
	Semi-annual	0.41	0.46	0.55	0.47	0.55	0.52	0.56	0.52	0.49	0.40	0.42	0.40	0.41
	Annual	0.41	0.46	0.55	0.47	0.55	0.52	0.56	0.52	0.49	0.40	0.42	0.41	0.42
	18 months	0.42	0.46	0.55	0.47	0.55	0.52	0.56	0.52	0.49	0.41	0.43	0.41	0.42
	2 years	0.41	0.46	0.56	0.47	0.55	0.52	0.56	0.52	0.49	0.41	0.43	0.41	0.42
	3 years	0.42	0.46	0.55	0.48	0.55	0.52	0.56	0.53	0.49	0.42	0.43	0.42	0.43
	4 years	0.42	0.46	0.55	0.47	0.55	0.52	0.56	0.53	0.50	0.42	0.43	0.42	0.43
	5 years	0.43	0.46	0.55	0.47	0.55	0.52	0.56	0.52	0.50	0.41	0.42	0.42	0.43
Buy and hold	0.52	0.46	0.54	0.46	0.56	0.52	0.58	0.54	0.47	0.43	0.45	0.46	0.45	
1976 - 1985	Monthly	0.45	0.45	0.64	0.47	0.54	0.52	0.55	0.52	0.70	0.39	0.46	0.48	0.47
	Quarterly	0.45	0.45	0.64	0.47	0.54	0.52	0.55	0.52	0.71	0.38	0.46	0.48	0.47
	Semi-annual	0.45	0.46	0.64	0.47	0.54	0.53	0.56	0.52	0.71	0.39	0.46	0.48	0.47
	Annual	0.46	0.45	0.64	0.47	0.54	0.53	0.56	0.52	0.70	0.39	0.46	0.48	0.47
	18 months	0.45	0.45	0.64	0.47	0.55	0.52	0.57	0.52	0.71	0.39	0.47	0.48	0.47
	2 years	0.46	0.45	0.64	0.47	0.55	0.52	0.56	0.53	0.71	0.39	0.46	0.49	0.48
	3 years	0.45	0.45	0.65	0.48	0.55	0.52	0.57	0.52	0.71	0.39	0.46	0.49	0.47
	4 years	0.47	0.46	0.65	0.47	0.56	0.51	0.57	0.53	0.72	0.39	0.46	0.50	0.49
	5 years	0.49	0.47	0.67	0.50	0.56	0.54	0.58	0.54	0.72	0.39	0.46	0.52	0.52
Buy and hold	0.49	0.44	0.69	0.44	0.59	0.52	0.61	0.52	0.71	0.38	0.45	0.48	0.46	
1986 - 1995	Monthly	0.48	0.55	0.64	0.57	0.61	0.63	0.63	0.60	0.46	0.50	0.55	0.45	0.48
	Quarterly	0.49	0.56	0.65	0.57	0.62	0.63	0.63	0.61	0.46	0.50	0.55	0.46	0.49
	Semi-annual	0.49	0.56	0.65	0.57	0.62	0.63	0.63	0.61	0.46	0.50	0.55	0.45	0.48
	Annual	0.49	0.55	0.65	0.56	0.61	0.62	0.63	0.61	0.46	0.50	0.55	0.46	0.48
	18 months	0.49	0.55	0.65	0.56	0.62	0.63	0.63	0.61	0.46	0.50	0.55	0.46	0.49
	2 years	0.49	0.56	0.65	0.57	0.62	0.63	0.63	0.61	0.46	0.50	0.56	0.46	0.49
	3 years	0.51	0.56	0.65	0.57	0.61	0.63	0.63	0.61	0.46	0.50	0.55	0.47	0.50
	4 years	0.51	0.56	0.64	0.57	0.61	0.62	0.62	0.61	0.46	0.50	0.55	0.48	0.50
	5 years	0.52	0.57	0.64	0.58	0.61	0.62	0.63	0.61	0.48	0.51	0.56	0.50	0.53
Buy and hold	0.54	0.57	0.63	0.57	0.61	0.62	0.63	0.62	0.47	0.51	0.56	0.50	0.53	
1996 - 2005	Monthly	0.36	0.29	0.57	0.48	0.61	0.59	0.61	0.51	0.46	0.36	0.32	0.37	0.44
	Quarterly	0.35	0.29	0.57	0.48	0.61	0.60	0.61	0.52	0.46	0.36	0.32	0.38	0.45
	Semi-annual	0.35	0.29	0.58	0.47	0.61	0.59	0.62	0.52	0.46	0.36	0.32	0.37	0.44
	Annual	0.36	0.29	0.58	0.49	0.61	0.59	0.62	0.52	0.46	0.38	0.32	0.39	0.46
	18 months	0.36	0.29	0.59	0.49	0.62	0.61	0.63	0.53	0.46	0.39	0.32	0.40	0.47
	2 years	0.37	0.30	0.59	0.50	0.62	0.60	0.64	0.54	0.46	0.41	0.33	0.39	0.47
	3 years	0.35	0.29	0.57	0.46	0.60	0.58	0.61	0.52	0.47	0.39	0.31	0.35	0.40
	4 years	0.37	0.30	0.59	0.51	0.62	0.61	0.63	0.56	0.47	0.43	0.33	0.40	0.47
	5 years	0.36	0.30	0.56	0.46	0.60	0.58	0.61	0.52	0.48	0.40	0.32	0.37	0.42
Buy and hold	0.39	0.31	0.56	0.46	0.60	0.56	0.62	0.53	0.46	0.44	0.33	0.40	0.44	
2006 - 2015	Monthly	0.35	0.53	0.37	0.37	0.43	0.36	0.43	0.43	0.36	0.35	0.37	0.30	0.27
	Quarterly	0.35	0.53	0.37	0.37	0.43	0.36	0.43	0.43	0.36	0.36	0.37	0.30	0.28
	Semi-annual	0.35	0.54	0.37	0.38	0.43	0.36	0.43	0.43	0.36	0.36	0.37	0.31	0.28
	Annual	0.36	0.54	0.37	0.38	0.43	0.36	0.43	0.43	0.36	0.36	0.38	0.31	0.28
	18 months	0.37	0.54	0.37	0.38	0.43	0.36	0.43	0.43	0.36	0.36	0.38	0.31	0.29
	2 years	0.35	0.53	0.37	0.37	0.43	0.36	0.43	0.42	0.36	0.36	0.37	0.30	0.27
	3 years	0.36	0.54	0.37	0.36	0.43	0.36	0.43	0.42	0.36	0.36	0.38	0.31	0.28
	4 years	0.35	0.53	0.36	0.37	0.43	0.36	0.43	0.42	0.36	0.36	0.37	0.30	0.28
	5 years	0.36	0.53	0.36	0.37	0.42	0.36	0.42	0.42	0.36	0.36	0.37	0.31	0.28
Buy and hold	0.38	0.53	0.36	0.35	0.42	0.36	0.42	0.42	0.36	0.35	0.38	0.31	0.29	

into deciles – each sorting variable thus produces ten different factor portfolios.

We perform a rebalancing exercise on our set of underlying portfolios and we use

9 different rebalancing periods, from one month to five years. To be more precise, in the exhibit below, each column represents a rebalancing exercise done with a set of ten portfolios (underlying constituents)

## 4) The Rebalancing Fantasy: "Smart Beta outperforms because it trades against mean reversion"

that are due to univariate decile sorts on 13 different sorting variables, from Momentum to Variance, indicated in the column header. The analysis is done for 40 years spanning 1976 - 2015 and is further broken down into 4 subsamples, each of 10 years length. The rebalancing exercise is compared to a buy and hold portfolio in each case. At the start of each period (be it the whole 40 year sample or any of the 10 year sub-samples), all the portfolios are initially equal-weighted and then rebalanced at the corresponding frequency. Buy-and-hold portfolios are never rebalanced and are allowed to drift depending on the performance of the assets. Our findings are consistent with Qian (2014) – the superiority of a rebalanced portfolio is by no means guaranteed. Our results, reported below, indicate that there is no clear relationship between the rebalancing interval and performance.

The table shows that, for many sets of assets, increasing the rebalancing frequency actually reduces performance over the forty year sample period. It should also be noted that results for the same asset menu often differ widely across sub-samples. Overall, our results suggest that rebalancing does not necessarily add value. Instead, whether or not rebalancing adds value depends on the time period and asset menu at hand. In addition to this dependence of the sign and magnitude of the rebalancing effect on the set of constituent assets and prevailing market conditions, it is also worth noting that even when rebalancing adds value over the buy-and-hold strategy, performance may not necessarily increase with higher rebalancing frequencies. Thus, in addition to the uncertainty of whether there will be any rebalancing advantage over buy and hold, there is additional uncertainty with respect to the

optimal rebalancing frequency. In short, our empirical results suggest that neither rebalancing (as opposed to being buy and hold) nor increasing the frequency of rebalancing will necessarily add value.

We performed similar tests<sup>70</sup> using stock selections based on double sorting, industry portfolios based on different breakdowns of the stock universe into industries and also looked at rebalancing between 21 different country portfolios. As for the tests presented above, we found no clear relationship between the rebalancing interval and performance and could not ascertain whether rebalancing adds value over a buy and hold strategy or the other way around. Our tests over 36 different datasets containing different asset menus suggest that rebalancing effects are highly sensitive to the asset menu and the time period.

### Empirical Test II: Equal weighting with different rebalancing frequencies

It is often argued that equal-weighted strategies in particular are a perfect illustration of a Smart Beta strategy that is driven by rebalancing. We therefore focus on equal weighting in our next (acid) test. We assess the factor exposures of equal weighted returns to standard factor models (which do not contain any rebalancing factor). If equal weighting leads to a positive rebalancing effect, the strategy should thus provide returns over and above what can be explained by standard factors. In other words, our analysis looks at whether the factor models fully explain the returns of equal-weighted portfolios or whether equal weighting creates an alpha relative to these models.

70 – These results are available upon request

## 4) The Rebalancing Fantasy: "Smart Beta outperforms because it trades against mean reversion"

Empirical finance research has come up with a range of "reversal factors", which correspond to strategies that move out of stocks that have experienced strong relative price appreciation and into stocks that have recorded weak returns relative to the average stock. In addition to analysing the factor exposure of equally-weighted portfolios using standard models, we also rely on a factor model that includes both short- and long-term reversal factors as proxies for measuring the rebalancing effect. To be more specific, the factor models that we compare are:

A. A Fama French-type factor model that features the Market, Value and Small Cap factors

B. A Carhart-type factor model that also includes Momentum in addition to the previous three factors

C. A Combined model that features the factors from the Carhart four factor model plus the short and long term reversal factors - the former is based on returns in the most recent month and the latter uses returns over the last five years, excluding the most recent one<sup>71</sup> - note that there is no overlap with the Momentum factor which is based on the last twelve months, excluding the most recent one.

In particular, Model C, the Carhart model augmented by reversal factors will allow us to assess the exposures to reversal factors and permit conclusions as the *marginal* impact of these factors on portfolio returns given that the impact of the other factors (market, size, value and momentum, which are also included in this model) has been accounted for. Moreover, we are able to assess the added value of the rebalancing factors in explaining portfolio returns by comparing the R-squared obtained for the established Carhart factor model (Model B) and the model that has been augmented with the reversal factors (Model C).

In addition to including such reversal factors, we employ a second element in our test design to obtain evidence on the relevance of rebalancing effects: Specifically, we vary the rebalancing frequency of the equal-weighted portfolios to ascertain whether higher frequencies of rebalancing lead to differences in results. We test monthly, quarterly, yearly rebalancing and rebalancing every five years. If rebalancing is the main driver of Smart Beta strategies' performance, one would expect that more of it would produce higher returns or alpha.

We form periodically rebalanced equal-weighted test portfolios containing the 500 largest US stocks from the CRSP database and analyse results for the period from 1974 to 2014. Results are reported in Exhibit 8.

It is worth noting that the annualised relative returns over the 40 years of analysis are largely invariant with the frequency of rebalancing. In terms of relative returns, there are no benefits from rebalancing more often. The exhibit also shows annualised alpha from the different factor models.

Monthly, quarterly and yearly rebalancing frequencies result in Value and Small Cap tilts but do not produce statistically significant annualised alpha in the context of the three-factor model (Panel A).

The introduction of the Momentum factor has a marked impact on the results: annualised alphas from the four-factor model are now significant at higher rebalancing frequencies. The finding of a positive four factor alpha for high frequency rebalancing of equal-weighted strategies is in line with results from Plyakha, Uppal and Vilkov (2014)<sup>72</sup>. Overall,

71 - Short-term reversal factor is the return difference between past month losers and past month winners, long-term reversal factor is the return of losers minus return of winners over the last 5 years excluding the most recent year, based on definitions used in Kenneth French's data library.

72 - The authors examine monthly rebalanced EW strategy along with the value- and price-weighted strategies. Plyakha et al. find that the rebalanced portfolio outperforms the value weighted portfolio, in line with our results. They find Carhart four factor alpha of 1.75% for the EW strategy which is similar to the 1.45% from our results. However, contrary to our study, they do not consider a simpler Fama-French three factor model. The negative Momentum exposure, found in both theirs and our studies is

## 4) The Rebalancing Fantasy: "Smart Beta outperforms because it trades against mean reversion"

### Exhibit 8: Periodically rebalanced strategies – alpha measurement and factor exposure

This Exhibit shows the results of periodically rebalanced portfolios based on 500 US stocks. The portfolios are rebalanced every month, quarter, year or 5 years and equal weighting is applied. The results are based on daily total returns during the period from 31 December 1974 to 31 December 2014. The Market factor is the excess returns of the CRSP S&P-500 index over risk free rate. The yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. The SMB, HML, MOM and both reversal factors are obtained from Kenneth French's data library. Statistics are annualised. Regression coefficients significant at the 95% level are highlighted in bold. Newey-West robust standard errors are employed.

Equal weighted periodically rebalanced portfolios based on Top 500 US stocks				
	Monthly rebalancing	Quarterly rebalancing	Yearly Rebalancing	5 Year rebalancing
Ann. Rel. Returns	2.85%	2.78%	2.82%	2.85%

#### Panel A: Fama and French Three-Factor Model

Ann. Alpha	0.48%	0.53%	0.69%	<b>1.36%</b>
Mkt-Rf	<b>1.04</b>	<b>1.03</b>	<b>1.02</b>	<b>0.98</b>
SMB	<b>0.26</b>	<b>0.26</b>	<b>0.25</b>	<b>0.19</b>
HML	<b>0.26</b>	<b>0.25</b>	<b>0.24</b>	<b>0.18</b>
R-squared	96.20%	96.13%	96.30%	95.75%

#### Panel B: Carhart Four-Factor Model

Ann. Alpha	<b>1.45%</b>	<b>1.39%</b>	0.99%	0.80%
Mkt-Rf	<b>1.03</b>	<b>1.02</b>	<b>1.02</b>	<b>0.99</b>
SMB	<b>0.26</b>	<b>0.25</b>	<b>0.25</b>	<b>0.19</b>
HML	<b>0.22</b>	<b>0.22</b>	<b>0.22</b>	<b>0.20</b>
MOM	<b>-0.10</b>	<b>-0.09</b>	<b>-0.03</b>	<b>0.06</b>
R-squared	96.59%	96.44%	96.33%	95.89%

#### Panel C: Augmented Model

Ann Alpha	<b>1.25%</b>	<b>1.75%</b>	<b>1.20%</b>	0.83%
Mkt-Rf	<b>1.03</b>	<b>1.02</b>	<b>1.02</b>	<b>0.99</b>
SMB	<b>0.25</b>	<b>0.25</b>	<b>0.25</b>	<b>0.19</b>
HML	<b>0.22</b>	<b>0.21</b>	<b>0.21</b>	<b>0.20</b>
MOM	<b>-0.10</b>	<b>-0.09</b>	<b>-0.04</b>	<b>0.06</b>
ST Reversal	<b>0.01</b>	<b>-0.02</b>	<b>-0.01</b>	0.00
LT Reversal	<b>0.02</b>	<b>0.02</b>	<b>0.04</b>	0.01
R-squared	96.59%	96.45%	96.36%	95.89%
Δ in R-Squared w.r.t. Panel B	0.01%	0.01%	0.03%	0.00%

however, the fact that results depend on the factor model chosen suggests that higher frequency rebalancing does not necessarily add alpha. In fact, sizable alpha only arises in high frequency equal weighted strategies because Momentum exposure becomes negative while returns remain relatively stable.

Moreover, the exposure of the equally-weighted strategies to the rebalancing factors from Panel C is either negative, statistically insignificant or not economically significant suggesting that

these simple Smart Beta strategies do not draw their performance from exposure to such reversal factors. For example, the monthly rebalanced strategy has exposure to the short-term reversal factor of 0.01, to the long-term reversal factors of 0.02, which pale against the size (SMB) and Value (HML) exposures, which stand at 0.25 and 0.22, respectively.

In addition to these low beta coefficients of the test strategies with respect to the reversal factors, we also observe an almost non-existent "improvement" in

likely responsible for the difference in alphas between the Carhart and Fama French models. As they decrease the rebalancing frequency, the four factor alpha decreases as well to 1.17% in the case of 6 month rebalancing frequency and to 0.8% for the annually rebalanced strategy. We find a similar pattern of decreasing alpha. Our results in terms of Sharpe ratios also align well with their paper. The different rebalancing frequencies in their study bear no clear relation to the performance – the Sharpe Ratios oscillate from 0.43 for 1 month frequency, 0.41 for 6 month frequency to 0.44 for annual rebalancing. Our study (Empirical Test I) does not find a clear relationship between rebalancing frequency and Sharpe ratios either.

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the explanatory power of the augmented model compared to the Carhart model, as measured by R-squared. The difference in R-squared between the augmented model and the Carhart four-factor model is largely negligible, with a difference in R-squared in the order of 0.01% resulting from the addition of the two reversal factors.

In the end, we find no support for the claim that rebalancing explains away the outperformance of equal-weighted indices; at best the contribution of "reversal factors" appears to be marginal.

### Empirical Test III: Comparing the exposure of factor-tilted portfolios

Another way of assessing the importance of rebalancing in Smart Beta strategies is to investigate the performance and factor exposure (or multi-factor alpha) of factor-tilted portfolios. We investigate the explanatory power of the reversal factors in a similar fashion to the Empirical Test II – by comparing the beta coefficients and explanatory power of a Carhart-type factor model with those of an extended model that features both the short- and long-term reversal factors along the four factors from the Carhart-type model. Analysing factor exposure of simple factor-tilted portfolios will allow us to directly compare the importance of the dominant factor tilts and the exposure to the reversal factors. Since the objective of factor-tilted portfolios is to capture the risk premium associated with a factor tilt, we would expect the reversal factor tilts to be unimportant relative to the target factor tilt and the other mainstream factors.

The following exhibit shows factor exposure and alpha of factor-tilted portfolios in the context of the two models and for

a 40-year period (1974-2014). We study factor-tilted portfolios coming from Kenneth French's database, in particular the popular factors of Momentum, Value and Size. We compare both the equally-weighted and cap-weighted daily returns of these portfolios and try to investigate whether reversal factors have any meaningful impact on them. We also include the quarterly rebalanced equally-weighted portfolio of the top 500 U.S. stocks from the previous illustration in the interest of comparison. For a more detailed explanation of the construction of the portfolios, we refer the reader to the header in Exhibit 9 and beyond to Kenneth French's website<sup>73</sup>. It should be noted that the equal-weighted factor tilted portfolios from Kenneth French are rebalanced daily and thus do not correspond to approaches that would actually be used in Smart Beta indices, which typically rebalance at most at quarterly. Therefore, relative to actual Smart Beta strategies, our results may overstate the importance of the short-term reversal factor which could be in part captured by such high-frequency rebalancing.

Nevertheless, our results below show that that the exposure to standard factors of these test portfolios is incomparably more important than their exposure to the reversal factors. This can be seen from the fact that the magnitude of factor exposures for target factors (respectively size, value and momentum) is much higher than any exposure to the long or short-term reversal factors. Moreover, we can see that the goodness of fit (R-squared) of the augmented model barely increases relative to the four factor model for most of the portfolios, suggesting that adding the two reversal factors does not help to capture more of the variability returns of alternative strategies.

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### Exhibit 9: Multi-Factor Models of alternative strategies including simple factor-tilted portfolios

The results are based on daily total returns during the period from 31 December 1974 to 31 December 2014. The test portfolios are as follows: EW Quarterly Rebalanced portfolio is constructed from 500 US Stocks by rebalancing to EW quarterly, the other portfolios proceed from Kenneth French's data library. The Big High Momentum portfolio is taken from the 2x3 bivariate sorts based on Market Cap and Prior Returns - the intersection of Big portfolios based on Market Cap (top 50%) and High Prior Returns portfolio based on prior (2-12) return (top 30%). The Big Value portfolio is taken from the 2x3 bivariate sorts based on Market Cap and Book-to-Market - the intersection of Big portfolios based on Market Cap (top 50%) and High Book-to-Market portfolios (top 30%). The Medium Market Cap portfolio is based on univariate sort based on Market Cap and represents the middle 40%. The Market factor is the excess returns of the CRSP S&P-500 index over risk free rate. The yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. The SMB, HML, MOM and reversal factors are obtained from Kenneth French's data library. Statistics are annualised. Regression coefficients significant at the 95% level are highlighted in bold. Newey-West errors are used.

	Equal Weighted				Cap-Weighted		
	EW Quarterly Rebalanced	Big High Momentum EW	Big Value EW	Medium Market Cap EW	Big High Momentum CW	Big Value CW	Medium Market Cap CW
Ann. Rel. Returns	2.78%	4.95%	4.97%	3.82%	2.82%	1.98%	2.95%

#### Panel A: Carhart Four Factor Model

Ann. Alpha	<b>1.39%</b>	-0.45%	0.87%	<b>1.64%</b>	<b>-1.62%</b>	<b>-2.32%</b>	0.06%
Mkt-Rf	<b>1.02</b>	<b>1.07</b>	<b>1.02</b>	<b>1.03</b>	<b>1.05</b>	<b>1.06</b>	<b>1.01</b>
SMB	<b>0.25</b>	<b>0.59</b>	<b>0.39</b>	<b>0.91</b>	<b>0.20</b>	<b>0.17</b>	<b>0.82</b>
HML	<b>0.22</b>	<b>0.06</b>	<b>0.70</b>	<b>0.09</b>	<b>0.03</b>	<b>0.83</b>	<b>0.11</b>
MOM	<b>-0.09</b>	<b>0.39</b>	<b>-0.07</b>	<b>-0.14</b>	<b>0.46</b>	-0.01	0.01
R-squared	96.44%	93.95%	93.03%	95.48%	96.53%	95.30%	95.43%

#### Panel B: Augmented Model

Ann. Alpha	<b>1.75%</b>	<b>-1.93%</b>	-0.57%	-0.50%	<b>-2.04%</b>	<b>-3.19%</b>	-0.84%
Mkt-Rf	<b>1.02</b>	<b>1.06</b>	<b>1.01</b>	<b>1.02</b>	<b>1.05</b>	<b>1.05</b>	<b>1.00</b>
SMB	<b>0.25</b>	<b>0.59</b>	<b>0.39</b>	<b>0.92</b>	<b>0.21</b>	<b>0.17</b>	<b>0.82</b>
HML	<b>0.21</b>	<b>0.09</b>	<b>0.72</b>	<b>0.15</b>	<b>0.04</b>	<b>0.85</b>	<b>0.13</b>
ST Reversal	-0.02	<b>0.06</b>	<b>0.06</b>	<b>0.09</b>	0.02	<b>0.04</b>	<b>0.04</b>
MOM	<b>-0.09</b>	<b>0.40</b>	<b>-0.06</b>	<b>-0.12</b>	<b>0.46</b>	-0.01	0.01
LT Reversal	0.02	<b>-0.04</b>	<b>-0.03</b>	<b>-0.09</b>	-0.02	-0.02	<b>-0.03</b>
R-squared	96.45%	94.14%	93.22%	95.92%	96.55%	95.37%	95.51%
Δ in R-Squared w.r.t. Panel A	0.01%	0.19%	0.18%	0.45%	0.02%	0.07%	0.08%

We also note that the Momentum strategy which we included here can be considered an anti-rebalancing strategy, as it increases weights in past winners. The reward to such momentum-tilted strategies has been widely documented. While the contribution of the rebalancing effect to the performance of Smart Beta is elusive, there is indeed an anti-rebalancing effect in certain Smart Beta strategies, notably in Momentum-tilted strategies.

Overall, the results of this third series of tests confirm that reversal factors are certainly not the major return drivers of factor-tilted Smart Beta strategies and that their contribution pales in comparison

to that of the target factors and other mainstream factors.

### Conclusion

The rebalancing effect is frequently cited as a major source of Smart Beta performance. However, this claim does not stand up to scrutiny.

First, it is important to emphasise that rebalancing relates to a number of distinct concepts. We have thus assessed rebalancing effects from different angles drawing on the different concepts to provide perspective on the question of the importance of rebalancing effects for

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Smart Beta. Our results shed doubt over the importance of a rebalancing effect in Smart Beta strategies. In particular, our analysis of buy-and-hold portfolios versus portfolios that are rebalanced at different frequencies shows that whether or not one generates increased performance from rebalancing in fact depends on the return behaviour of the assets in the menu. Rebalancing may or may not lead to improved performance over buy-and-hold strategies depending on the asset menu and the time period. Even if positive rebalancing effects exist (beyond the diversification effect that arises even with independently and identically distributed assets), it is uncertain that Smart Beta strategies capture such effects. Contrary to the idea that rebalancing drives performance, our analysis suggests that rebalancing an equal-weighted strategy more often does not necessarily improve performance. Moreover, both short-term and long-term reversal effects are empirically unimportant to explain the performance of the various Smart Beta strategies we analysed.

However, allowing a strategy to readjust its weights back to target weights may be necessary to maintain the strategy as well as a diversified portfolio. The effect of diversification, going back to the works of Markowitz (1952) is much more thoroughly documented than rebalancing effects. It would make perfect sense to exploit the insights from modern portfolio theory to address the issue of diversification in the design of Smart Beta strategies. In the end, the focus on capturing the elusive rebalancing effects risks diverting attention from the readily available and sizable benefits of proper diversification.

Of course, rebalancing may be important, notably to maintain diversification or to

maintain target factor exposures. However, rebalancing in itself is not an empirically documented source of the performance of Smart Beta strategies. Promoting a false rebalancing effect on the back of the well documented mean reversion effect at the asset class level is dangerous because it suggests that poor performance of certain strategies which may be due to a lack of robustness are just the price to pay for bright future performance. Here again, such misconceptions on where Smart Beta performance comes from can have serious consequences for investment decision making.

# Part 2: Investability Hurdles

## 5) The Liquidity Concern: "Smart Beta requires holding positions in highly illiquid stocks"

### Overview of the Claim

By definition, Smart Beta strategies entail allocating to securities in proportions that differ from their capitalisation-weights in broad-market indices. Because of this, the liquidity aspects of Smart Beta portfolios are likely to be different from those of market benchmarks. This leads many to warn against the alleged illiquidity of Smart Beta strategies and some to claim that the outperformance of this investing approach is largely explained by increased illiquidity risks which are rewarded by higher returns. Since there is a strong positive relationship between market capitalisation and liquidity, Smart Beta strategies that over-represent lower size companies and/or apply weighting schemes that deconcentrate portfolios will indeed tend to have lower liquidity. Because equal-weighted portfolios maximise portfolio deconcentration, they have been easy targets for illiquidity arguments. For example, Kose & Moroz (2014)<sup>74</sup> argue that an equal weighting strategy incurs costs of high positions in less liquid stocks and Cheema (2015)<sup>75</sup> makes the same point. Siu (2015)<sup>76</sup> looks at the risk of illiquidity being confused for low volatility and finds that minimum-variance portfolios may suffer from severe liquidity problems, with some of his portfolios even requiring several months to trade.

It is important to acknowledge the importance of portfolio liquidity analysis and to understand not only the benefits but also the risks and specific costs related to the departure from the market cap weighting. However, there is little evidence to suggest that Smart Beta performance is entirely driven by illiquidity risk. In particular, while analyses of stylised Smart Beta strategies may frequently lead to

predictions of implementation challenges, Smart Beta strategies as implemented in practice offer feasible solutions to control liquidity without much impact on performance. That testing uncontrolled implementations of Smart Beta approaches leads to suggestions of implementation challenges should not be surprising. These analyses are helpful to the extent that they can improve due diligence on Smart Beta strategies by pointing in the direction of a possible problem area; however, they should not be relied upon to draw conclusions on Smart Beta strategies that integrate implementation rules.

### Illiquidity premium and its relation to the outperformance of Smart Beta strategies

Studies based on stock level measures of liquidity by Amihud and Mendelson (1986)<sup>77</sup>, Brennan and Subrahmanyam (1996)<sup>78</sup> and Datar et al. (1998)<sup>79</sup> have proven that illiquid stocks command higher returns in the form of an illiquidity premium. Research by Pastor and Stambaugh (2003)<sup>80</sup> shows that stocks with greater sensitivity to market-wide liquidity events also commands a higher return.

Liquidity refers to the ability to transact significant amounts with minimal immediate price impact. Total transactions costs for less liquid stocks will be higher than for more liquid stocks and hence the ability of an investment strategy to benefit from the illiquidity premium will depend largely on the investor's time horizon being sufficiently long to offset any increase in transactions costs associated with illiquid stocks.

74 - Kose, E. and M. Moroz. 2014. The High Cost of Equal Weighting. Research Affiliates Publication.

75 - Cheema, S. 2015. Smart Beta – An Introduction to Smart Beta and its uses. Russell Investments Research Paper.

76 - Siu, F. 2015. Tradability versus Performance: The Role of Liquidity in Minimum Variance Smart Beta Products. *The Journal of Index Investing* 6(1): 79-88.

77 - Amihud, Y. and H. Mendelson. 1986. Asset Pricing and the Bid-Ask Spread. *Journal of Financial Economics* 17(2): 223-249.

78 - Brennan, M.J. and A. Subrahmanyam. 1996. Market Microstructure and Asset Pricing: On the Compensation for Illiquidity in Stock Returns. *Journal of Financial Economics* 41(3): 441-464.

79 - Datar, V. T., N.Y. Naik and R. Radcliffe. 1998. Liquidity and Stock Returns: An Alternative Test. *Journal of Financial Markets* 1(2): 203-219.

80 - Pastor, L. and R. F. Stambaugh. 2003. Liquidity Risk and Expected Stock Returns. *Journal of Political Economy* 111(3): 642-685.

## 5) The Liquidity Concern: "Smart Beta requires holding positions in highly illiquid stocks"

However, the existence of an illiquidity premium and the observation that most Smart Beta portfolios will tend to have lower liquidity than the broad-market benchmarks do not constitute proof that Smart Beta outperformance is explained by investments in illiquid securities. Smart Beta strategies derive their outperformance from exposure to systematic risk factors and/or smart weighting.<sup>81</sup> Their outperformance persists even after introducing several liquidity checks and filters. Smart Beta strategies can thus be easily controlled for illiquidity risks while still retaining much of the benefits arising from alternative weighting schemes and factor exposure. We provide two empirical illustrations of how one can control portfolio for better implementation properties, and what the impact on performance is.

### Empirical illustration I – Using implementation rules for equal weighted portfolios

We show that the outperformance of strategies created by equal-weighting progressively more and more liquid stocks does not decrease linearly with increasing liquidity. We also show that even after introducing further liquidity and capacity constraints Smart Beta performance benefits remain. Below, we first turn to a discussion of liquidity issues with naive equal weighting approaches, before introducing common-sense adjustments to improve liquidity.

### Naive equal-weighting without liquidity adjustments

In the first exhibit below, we show the performance characteristics of quarterly rebalanced equal-weighted portfolios constructed using Scientific Beta Long Term USA data. These results are based on a

universe consisting of 500 stocks with data sourced from CRSP. At each rebalancing, we recompose six equally-weighted portfolios containing a fixed number of securities ranging from 500 to 250 (by steps of 50 securities), with these securities corresponding to the most liquid available in the universe; for example the portfolio of 250 securities is equally allocated to the first 250 securities ranked by liquidity score at the time of rebalancing.)

We define highly liquid stocks using the Scientific Beta liquidity score – the sum of stock's trading ratio z-score and trading volume z-score, both computed quarterly using data over the period covering the last four quarters. The median of the four quarterly values is considered for the z-score. The trading ratio of a stock is the ratio of the number of days that the stock is actually exchanged to the total number of business days. The trading volume of a stock is its average traded daily dollar volume over the four quarters preceding the rebalancing date<sup>82</sup>.

The metrics that we investigate in the following exhibit do not only provide information about the absolute and relative performance of the strategies but also shed light on how the liquidity selection affects investability. For example, Days to trade measure the average time it takes to trade a \$1bn portfolio given the weights and corresponding trading volumes of strategy constituents. As the exhibit reveals, the intuitive expectation that a portfolio composed of more liquid stocks will be easier to trade is indeed confirmed by the data.

Since Smart Beta strategies deviate from the cap-weighted benchmarks, one of the key challenges is to preserve the tradability of the index with respect to the benchmark.

<sup>81</sup> – ERI Scientific Beta's Smart Factor Indices draw their performance from both factor tilting and superior diversification by smart weighting.

<sup>82</sup> – More details about the liquidity and capacity measures employed by ERI Scientific Beta can be found in the Universe Construction Rules available on [www.scientifbeta.com](http://www.scientifbeta.com)

## 5) The Liquidity Concern: "Smart Beta requires holding positions in highly illiquid stocks"

To measure this, we investigate two important ratios. The first ratio measures the *Holding multiple*, i.e. the ratio of asset weight in the alternative strategy to its weight in the cap weighted benchmark. This ratio can give us a better idea of how the alternative strategy deviates from the benchmark in terms of investment in the stocks with small market capitalisation, which are typically less liquid. A high ratio, if left unchecked and unaccounted for, could potentially indicate implementation problems. Similarly, the second ratio measures the *Trading multiple*, i.e. how the change in constituent weight at the rebalancing date relates to its weight in the benchmark. Again, a high ratio could signal problems with practical aspects of the trading required to keep the replicating

portfolio in line with the calculated target weights.

The rationale behind these two measures is that a strategy may be difficult and/or costlier to implement if, for a given constituent, the weight is high or the weight change at rebalancing is high relative to the market cap weight of that stock. This is because, even though the market cap is not a liquidity measure per se, it has been shown that liquidity is positively related to market cap and that trading costs are negatively related to market cap. For example, Keim and Madhavan (1997)<sup>83</sup> show that trading costs are positively related to trade size relative to market cap, which suggests that a high Trading multiple implies a high transaction

*Exhibit 10: Performance of quarterly rebalanced portfolios based on high liquidity selection*

*We form test portfolios with the top 500 US stocks from the CRSP database. The SciBeta US Long-Term Track Record Capitalisation-Weighted index is used as the benchmark. The yield on Secondary US Treasury bills (3M) is used as the proxy for risk-free rate. The analysis is done using weekly USD total return data. Each quarter we select and equal weight the top n stocks based on liquidity score. The Scientific Beta liquidity score is the sum of a stock's trading ratio z-score and trading volume z-score, both computed quarterly using data over the period covering the previous four quarters. The median of the four quarterly values is considered for the z-score. The trading ratio of a stock is the ratio of the number of days that the stock is actually exchanged to the total number of business days. The trading volume of a stock is its average traded daily dollar volume. Average capacity is the time series average of the cross-sectional weighted average of security weights and market capitalisations. Days to trade refers to the time it takes to trade a \$1 bn portfolio given security weights and assuming 10% of the average daily dollar trading volume can be traded. Due to data availability, the period of Days to trade calculation is restricted to the last 10 years of the sample. Average of 95th percentile days to trade is calculated by first considering the 95th percentile of days to trade at every quarter and then averaging this across quarters. Average 95th percentile of Holding weight multiple is calculated as the time series average (across quarters) of 95th percentile of the ratio of portfolio stock weight to its weight in the cap-weighted benchmark. Average 95th percentile of the Trading multiple is calculated as the time series average (across quarters) of 95th percentile of the ratio of portfolio stock weight change between two consecutive quarters to its weight in the cap-weighted benchmark.*

31/12/1974 – 31/12/2014	Quarterly Rebalanced EW Portfolios based on high liquidity selection					
	500 Stocks	450 Stocks	400 Stocks	350 Stocks	300 Stocks	250 Stocks
Ann. Returns	14.93%	14.69%	14.40%	14.00%	13.62%	13.29%
Ann. Volatility	17.02%	17.16%	17.25%	17.41%	17.60%	17.79%
Sharpe Ratio	0.58	0.56	0.54	0.51	0.48	0.46
Ann. Excess Returns	2.78%	2.53%	2.24%	1.84%	1.46%	1.13%
Tracking Error	4.78%	4.62%	4.37%	4.20%	4.07%	4.03%
Information Ratio	0.58	0.55	0.51	0.44	0.36	0.28
Average Capacity (\$M)	12,117	13,225	14,553	16,129	18,046	20,533
Ann. Average 1-way turnover	25.02%	27.90%	29.96%	32.04%	34.50%	36.35%
Average 95th percentile of Days to trade	0.79	0.57	0.48	0.43	0.41	0.40
Average 95th percentile of Holding multiple	14.92	10.60	8.40	7.64	7.50	7.66
Average 95th percentile of Trading multiple	2.42	2.06	1.92	1.97	2.19	2.51

83 - Keim, D. B., and Madhavan, A. 1997. Transactions costs and investment style. *Journal of Financial Economics*, 46(3), 265-292.

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cost. Moreover, they show that transaction costs are negatively related to market cap, which justifies our Holding multiple approach.

The measures described above are captured at every rebalancing by calculating the extreme end of the distribution of the ratio value for all individual assets. In this case, we take the 95th percentile as a reasonable proxy of the far end of the value. After collecting these percentile values for every rebalancing period, the final statistic is obtained by computing the average across time. These statistics will be important later on when we introduce liquidity adjustments that draw directly from the insights gained from these measures. Exhibit 10 reports the measures for strategies that do not employ any liquidity adjustments whereas Exhibit 11 presents the same metrics after such controls have been introduced to ease implementation issues.

As we can observe, the claim that illiquidity premium is the only driver of Smart Beta outperformance is not supported. Equal-weighted portfolios of increasingly liquid securities retain positive excess returns. If illiquidity were the only performance driver of Smart Beta strategies, this excess return would disappear. While it appears that the excess return is indeed a decreasing function of liquidity, it is also clear that liquidity issues dissipate much faster than returns decrease - as evidenced by the precipitous drop in the average of 95th percentile of Days to trade - as one selects more and more liquid stocks.

### Introducing liquidity adjustments

Next we investigate portfolios constructed using the same methodology, but incorporating liquidity rules to ease implementation. These liquidity rules

correspond to the adjustments made in the construction process of the Scientific Beta developed market indices. This approach firstly limits the maximum weight of individual securities in the strategies by imposing an upper bound of 10 times a security's weight in the capitalisation-weighted benchmark for the universe. This is done to prevent large holdings in small stocks. After this cap is implemented, individual weight changes at quarterly rebalancing are limited so that they are not larger than the security's benchmark weight. This is meant to prevent large rebalancing trades in small stocks<sup>84</sup>.

The comparison between the exhibits 10 and 11 shows that we can easily implement liquidity-improving rules to ease implementation of the strategy with just a small impact on its performance. When moving from an unconstrained strategy to a strategy that implements relative holding and trading caps, whatever the severity of prior filtering-out of the less liquid stocks, liquidity characteristics improve markedly while the bulk of the performance is preserved. Smart Beta performance remains economically significant even when real-world liquidity constraints are implemented.

Exhibit 12 provides a summary of these results. It is interesting to compare the impact that the implementation rules have on reducing implementation issues and on performance. We can see for example that, through implementation rules, one can reduce the extreme implementation difficulties reflected in the average 95th percentile of the Days to trade measure from 0.79 for the naive implementation of the equally-weighted portfolio of the top 500 US stocks to a level of 0.46 when using the 400 most liquid stocks and employing liquidity enhancing holding and trading rules.

84 - Note that this adjustment is made only after the capping of the asset weight to 10 times its benchmark weight. Therefore, the second adjustment, which might be more prohibitive, may cause that some asset weights will be more than 10 times their benchmark weights, hence leading to small deviations from a strict value corresponding to adjustment number one.

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*Exhibit 11: Performance of quarterly rebalanced portfolios based on high liquidity selection with liquidity constraints*

We form test portfolios with the top 500 US stocks from the CRSP database. The SciBeta US Long-Term Track Record Capitalisation-Weighted index is used as the benchmark. The yield on Secondary US Treasury bills (3M) is used as the proxy for risk-free rate. The analysis is done using weekly USD total return data. Each quarter we select and equal weight the top n stocks based on liquidity score. We define highly liquid stocks using the Scientific Beta liquidity score - the sum of its trading ratio z-score and trading volume z-score, both computed quarterly using data over the period covering the last four quarters. The median of the four quarterly values is considered for the z-score. The trading ratio of a stock is the ratio of the number of days that the stock is actually exchanged to the total number of business days. The trading volume of a stock is its average traded daily dollar volume. Average capacity is the time series average of cross-sectional weighted average of security weight and its market capitalisation. Days to trade refers to the time it takes to trade a \$1 bn portfolio given security weights and assuming 10% of the average daily dollar trading volume can be traded. Average of 95th percentile Days to trade is calculated by first considering the 95th percentile of days to trade at every quarter and then averaging this across quarters. Due to data availability, the period of Days to trade calculation is restricted to the last 10 years of the sample. Average 95th percentile of the Holding weight multiple is calculated as the time series average (across quarters) of 95th percentile of the ratio of portfolio stock weight to its weight in the cap-weighted benchmark. Average 95th percentile of the Trading multiple is calculated as the time series average (across quarters) of 95th percentile of the ratio of portfolio stock weight change between two consecutive quarters to its weight in the cap-weighted benchmark. The constraints are as follows. Security weight is first capped to 10 times its benchmark weight. After this, the change in security weights is limited to the benchmark weights. This constraint can lead to some weights breaking the first constraint.

31/12/1974 – 31/12/2014	Quarterly Rebalanced EW Portfolios based on high liquidity selection and after the introduction of liquidity constraints					
	500 Stocks	450 Stocks	400 Stocks	350 Stocks	300 Stocks	250 Stocks
Ann. Returns	14.74%	14.58%	14.23%	13.77%	13.47%	13.03%
Ann. Volatility	16.84%	16.93%	17.02%	17.14%	17.27%	17.43%
Sharpe Ratio	0.57	0.56	0.54	0.51	0.48	0.45
Ann. Excess Returns	2.58%	2.42%	2.08%	1.61%	1.31%	0.88%
Tracking Error	4.43%	4.25%	3.98%	3.74%	3.50%	3.37%
Information Ratio	0.58	0.57	0.52	0.43	0.37	0.26
Average Capacity (\$M)	12,526	13,734	15,210	16,945	19,116	21,889
Ann. Average 1-way turnover	21.66%	23.68%	25.45%	27.21%	28.99%	30.23%
Average 95th percentile of Days to trade	0.77	0.54	0.46	0.43	0.41	0.41
Average 95th percentile the Holding multiple	10.98	8.60	7.10	6.37	6.11	6.28
Average 95th percentile of the Trading multiple	0.99	1.00	1.00	1.00	1.00	1.00

*Exhibit 12: Comparison between unconstrained and constrained versions of the test portfolios*

The table shows the comparison of annualised returns, excess returns, average of 95th percentile of Days to trade and the average of the 95th percentile of the Trading multiple between the unconstrained and constrained version of the test portfolios developed above. We form test portfolios with the top 500 US stocks from the CRSP database. The SciBeta US Long-Term Track Record Capitalisation-Weighted index is used as the benchmark. The yield Secondary US Treasury bills (3M) is used as the proxy for risk-free rate. Each quarter we select and equal weight top n stocks based on liquidity score. The constraints are as follows. Security weight is first capped to 10 times its benchmark weight. After this, the change in security weights is limited to the benchmark weight.

Quarterly Rebalanced EW Portfolios based on high liquidity selection

31/12/1974 – 31/12/2014	Ann. Returns		Ann. Excess Returns		Average 95th percentile of Days to trade		Average 95th percentile of the Trading multiple	
	Unconstrained	Constrained	Unconstrained	Constrained	Unconstrained	Constrained	Unconstrained	Constrained
500 Stocks	14.93%	14.74%	2.78%	2.58%	0.79	0.77	2.42	0.99
450 Stocks	14.69%	14.58%	2.53%	2.42%	0.57	0.54	2.06	1.00
400 Stocks	14.40%	14.23%	2.24%	2.08%	0.48	0.46	1.92	1.00
350 Stocks	14.00%	13.77%	1.84%	1.61%	0.43	0.43	1.97	1.00
300 Stocks	13.62%	13.47%	1.46%	1.31%	0.41	0.41	2.19	1.00
250 Stocks	13.29%	13.03%	1.13%	0.88%	0.40	0.41	2.51	1.00

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More prominently, the liquidity adjustments bring benefits in terms of limiting large trades relative to constituent market capitalisation which helps to bring down transactions costs (Keim and Madhavan (1997)). The Trading multiple – more specifically the average of its extreme values – is rather high for the unconstrained strategies, with values close to or in excess of 2 in all scenarios. When moving from the unconstrained strategy with 500 stocks to the more liquid version with 400 stocks and implementing the liquidity adjustments, this ratio falls by close to 59% (from 2.42 to 1). The annual relative return however only decreases by some 25% (from 2.78% to 2.08%). Thus even after severely reducing the implementation hurdles of the strategies, about 75 percent of the outperformance remains.

### Empirical Illustration II – Controlling the liquidity of Smart Beta products

Our next and final illustration explores the liquidity controls available in state-

of-the-art Smart Beta indices. Our results show that popular factor choices (namely Value, Mid Cap, High Momentum and Low Volatility) coupled with a Maximum Deconcentration weighting scheme (which represents a practical implementation of equal-weighting) continue to display excess returns even after applying a High-Liquidity filter to the stock selection. This filter retains the top 60% of securities by liquidity within the stock selection (that contains half the stocks in the parent universe where these stocks have higher than median factor scores). Note that all indices presented below employ the capping rules described in the previous empirical illustration.

The results in Exhibit 13 show that highly liquid versions of factor-tilted indices have lower outperformance than their standard counterparts. However, they maintain sizable performance benefits with annual relative returns ranging from 1.87% to 4.09%, compared to 2.83% to 4.52% for the indices without the high liquidity filter. The highly-liquid version of their equal-weighted combination adds 3.17%

*Exhibit 13: Performance comparison of Scientific Beta normal and highly-liquid versions of Maximum Deconcentration indices for single factor and Multi-Beta EW.*

*The SciBeta US Long-Term Track Record Capitalisation-Weighted index is used as the benchmark. The yield on Secondary US Treasury bills (3M) is used as the proxy for risk-free rate. The analysis is done using weekly USD total return data. The High-Liquidity filter selects 60% of securities with the highest liquidity score within each factor-based stock selection.*

Scientific Beta Long Term Track Record USA Indices – Maximum Deconcentration weighting scheme										
31/12/1974 – 31/12/2014	Value		Mid Cap		High Momentum		Low Volatility		Multi Beta (Equal Weight allocation to the four single-tilt indices)	
	Normal	High Liquidity filter	Normal	High Liquidity filter	Normal	High Liquidity filter	Normal	High Liquidity filter	Normal	High Liquidity filter
Ann. Returns	16.68%	15.91%	16.49%	16.25%	15.62%	14.56%	14.98%	14.03%	16.04%	15.33%
Ann. Volatility	17.40%	17.84%	18.25%	19.48%	16.92%	17.38%	14.57%	14.80%	16.46%	16.88%
Sharpe Ratio	0.66	0.61	0.62	0.57	0.62	0.54	0.68	0.60	0.66	0.61
Ann. Excess Returns	4.52%	3.75%	4.33%	4.09%	3.46%	2.41%	2.83%	1.87%	3.88%	3.17%
Tracking Error	6.23%	6.10%	7.30%	7.90%	4.59%	4.59%	5.67%	5.41%	4.94%	4.31%
Information Ratio	0.72	0.62	0.59	0.52	0.75	0.52	0.50	0.35	0.79	0.74

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per annum, which represents about 82% of the outperformance of its standard counterpart.

### Conclusion

Portfolio liquidity is one of the key considerations in investment management. Smart Beta strategies have been criticised for increased liquidity risks and some have asserted that their outperformance could be explained mainly by the existence of an illiquidity premium. Using a weighting approach known to be associated with implementation issues to serve as an acid test, we have shown that, while naively implemented Smart Beta strategies may obviously suffer from much reduced liquidity, the outperformance of Smart Beta strategies can be maintained while ensuring high liquidity and ease of implementation. Our empirical results suggest that selecting increasingly liquid stocks and introducing further liquidity enhancing holding and trading caps rules anchored on capitalisation weights improves liquidity and reduces implementation issues while preserving the bulk of the outperformance benefits of Smart Beta approaches. Observing the significant outperformance of Smart Beta indices that use such implementation rules suggests that target factor exposures and alternative weighting schemes, not the capture of an illiquidity premium, are the main drivers of the performance of Smart Beta strategies.

## 6) The Turnover Critique: "Smart Beta necessarily leads to high turnover"

### Overview of the claim

Cap-weighted market indices essentially represent buy-and-hold strategies. Aside from index reconstitutions due to corporate actions or large changes in (free-float) capitalisations that can lead to inclusions, exclusions or major weight adjustments, index weights evolve together with the prices of constituent securities to seamlessly adjust to targeted (capitalisation) weights. Smart Beta indices are produced by security selections and/or weighting schemes that result in constituent weights differing from the weights of these securities in capitalisation-weighted benchmarks of their universe. Periodic rebalancing is needed to maintain strategy weights and the trading activity generates additional turnover.

The fact that Smart Beta strategies do not have buy-and-hold weightings, has led some to warn that they may lead to excessive turnover. For example, Blitz (2012)<sup>85</sup>, among other things, criticises Smart Beta strategies on the ground that they can be inefficient from a turnover perspective. It has also been argued that some Smart Beta strategies may be implementable with low turnover, while others will necessarily come with excessive turnover. For example, promoters of fundamental equity indexation approaches argue that Smart Beta leads to excessive turnover except when it uses fundamental equity indexation. Chow et al. (2011)<sup>86</sup> examine set of Smart Beta approaches and report that the turnover of most of these is much higher than the turnover of fundamental-based strategies. It is important to note however that the authors simulate their own stylised versions of popular Smart Beta strategies instead of relying on the officially published index series from commercial providers. In doing so, they neglect the turnover controls and

other key implementation constraints built in third-party index strategies available on the market (see Amenc et al. (2011)<sup>87</sup> for a critical comment). A different dichotomy is introduced by Webster (2015)<sup>88</sup> who distinguishes between rules-based heuristics and optimisation-based indices and argues that while turnover constraints can readily be taken into consideration by an optimiser, it can be difficult to manage turnover for rules-based heuristic indices.

It is definitely useful to analyse the turnover of Smart Beta indices. Even if asserting a portfolio's turnover does not provide a precise measure for estimating the actual costs of trading, it provides an intuitive and parsimonious idea of the fund's trading activity and, as such, is a sensible indicator. However, one should probably take with a grain of salt claims that all Smart Beta indices have excessive turnover or that third-party approaches will necessarily lead to higher turnover than that being marketed by the provider with which a researcher is affiliated. It is indeed possible to support any arbitrary claim about the excessive turnover of a popular index by testing a version of its strategy that does not correspond to the index methodology and specifically omit turnover control. Commercial Smart Beta strategies typically include explicit or implicit turnover control and such controls can be applied to any strategy, whether optimisation- or heuristic-based. Moreover, for many strategies, such turnover controls can be implemented without much impact on performance.

### Overview of turnover control methods

Scherer (2010)<sup>89</sup> reviews methods of managing the transaction costs of portfolio construction and lists fixed periodic

85 - Blitz, D. 2012. How smart is Smart Beta Investing? Robeco White Paper for institutional investors.

86 - Chow, T. M., J. Hsu, V. Kalesnik and B. Little. 2011. A survey of alternative equity index strategies. *Financial Analysts Journal* 67(5): 37-57.

87 - Amenc, N., Goltz, F. and L. Martellini. 2011. A survey of alternative equity index strategies: A comment, *Financial Analysts Journal* 67(6): 14-19.

88 - Webster, J. 2015. The move to multi-factor investing: what every investor should know. Axioma Exchange Traded Funds Guide.

89 - Scherer, B. 2010. Portfolio construction and risk budgeting. 4th edition. Risk Books: London.

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rebalancing strategies, conditional optimal rebalancing strategies, and strategies with embedded explicit limits on turnover.

### Fixed rebalancing

In fixed calendar strategies, the portfolio is rebalanced at certain pre-specified intervals: for instance, monthly, quarterly, yearly. The simplest method of keeping turnover under control is to adjust the rebalancing frequency. All else equal, a lower (higher) rebalancing frequency will lead to lower (higher) transaction cost but also to greater (smaller) deviations from target weights between reviews.

For non-cap weighted indices, simply lowering the rebalancing frequency to adjust turnover will cause the performance of the index to depend on the market conditions around rebalancing dates, and thus strategy performance may become sensitive to choices of the rebalancing period. Blitz, van der Grient and van Vliet (2010)<sup>90</sup> show that the subjective choice of rebalancing dates may significantly affect index performance. Consequently, to attribute performance to strategies that rebalance at greater intervals, it may be necessary to take into account the impact of the choice of rebalancing date. A specific case of fixed rebalancing is called "staggered rebalancing" and involves slicing a portfolio or an index into a number of tranches that will be reviewed separately at different periods.

### Conditional or trigger rebalancing

The trigger approach consists in activating index review whenever the gap between the current weight and the new target weight of an index constituent reaches a specific threshold (e.g.  $\pm 2\%$  or  $\pm 5\%$ ).

The higher the threshold, the lower the turnover, but the greater the deviation from target weights.

Trigger strategies essentially create a no-trade region for each asset in the portfolio. However, the literature shows that these no-trade regions can also be defined based on overall weight changes in the portfolio (Atkinson, Pliska and Wilmott (1997)<sup>91</sup>; Donohue and Yip (2003)<sup>92</sup>; Martellini and Priaulet (2002)<sup>93</sup>; Leland (1999)<sup>94</sup>). Such turnover control rules give rise to optimal control strategies. These strategies will rebalance the portfolio in accordance with the weights coming from a strict application of the strategy only if a threshold of weight changes across the portfolio has been reached.

Below, we illustrate such an approach, drawing on the type of turnover control implemented by ERI Scientific Beta for its indices. These indices employ a conditional (or trigger) rebalancing approach based on insights from optimal control theory (see Martellini and Priaulet (2002) and Leland (1999)). The trigger approach activates rebalancing whenever the gap between the index current weights and new target weights reaches a specific threshold.

### Turnover Control: An illustration

We provide an illustration drawn from Amenc, Goltz, and Gonzalez (2014)<sup>95</sup> who analyse the results obtained with a range of Smart Beta indices before and after implementing turnover control. They analyse five widely used weighting schemes, namely Maximum Deconcentration (practical implementation of equal weighting), Maximum Decorrelation, Diversified Risk-weighted (a risk-parity approach), Minimum Volatility and

90 - Blitz, D., Van der Grient, B., and Van Vliet, P. 2010. Fundamental indexation: Rebalancing assumptions and performance. *Journal of Index Investing* 1(2): 82-88.

91 - Atkinson, C, S. Pliska and P. Wilmott. 1997. Portfolio management with transaction costs. *Proceedings of the Royal Society A* 453: 551-562

92 - Donohue, C., and K. Yip. 2003. Optimal portfolio rebalancing with transaction costs. *Journal of Portfolio Management* 29 (4): 49-63.

93 - Martellini, L. and P. Priaulet. 2002. Competing methods for option hedging in the presence of transaction costs. *Journal of Derivatives* 9(3): 26-38.

94 - Leland, H. 1999. Optimal asset rebalancing in the presence of transaction costs. U.C. Berkeley University Working Paper.

95 - Amenc, N., F. Goltz and S. Sivasubramanian. 2016. Investability of Scientific Beta Indices. ERI Scientific Beta White Paper (May).

## 6) The Turnover Critique: "Smart Beta necessarily leads to high turnover"

Maximum Sharpe Ratio weighting in a US large and mid cap universe over the period from 31/12/1973 to 31/12/2013. The results are reproduced in the exhibit below. Before turnover control, the various Smart Beta portfolios exhibit turnover that can exceed reasonable investability levels, averaging some 45% and peaking at about 65% average annualised one-way turnover. After implementing optimal turnover control, the same indices exhibit a much more reasonable level of turnover which averages some 30%. Most interestingly, the reduction in turnover is accompanied by marginal or no change in strategy average returns and volatility. For example, the returns of the higher turnover strategies experience marginal changes from 13.75% to 13.83%, 13.61% to 13.50% and 13.74% to 13.97%

to 14.03% for the Maximum Decorrelation, Efficient Minimum Volatility and Efficient Maximum Sharpe Ratio weighting schemes, respectively. Volatility also changes in a benign manner: from 16.83% to 16.74%, 14.30% to 14.39% and 15.96% to 15.79%, respectively. Over the five weighting schemes, turnover control results in an insignificant increase in gross performance (of 5 basis points per annum) and an insignificant decrease in volatility (of 3 basis points per annum).

However, if one looks at the performance net of trading costs, it is clear that turnover rules are beneficial, especially when trading costs are high. For example, the performance net of high trading costs (100 bps) of the Efficient Maximum Sharpe

*Exhibit 14: Comparison of performance, turnover and liquidity before and after turnover control*  
The first panel reports the statistics for the indices before any turnover control is applied, whereas the second panel reports the statistics for the indices after turnover control is applied. Returns and Volatility are calculated using daily total returns in the period 31/12/1973 to 31/12/2013 (40 years). Weighted Average Market Cap is the weighted average market capitalisation of the index in \$M over the 40-year period. Reported Turnover is one-way annualised. Turnover and Weighted Average Market Cap are average values across 160 quarters (40 years). The net returns of transaction costs are obtained using two levels of transaction costs - 20 bps per 100% 1-Way turnover and 100 bps per 100% 1-Way turnover. The first case corresponds to the worst case observed historically for the large and mid cap universe of our indices while the second case assumes 80% reduction in market liquidity and a corresponding increase in transaction costs. All statistics are annualised. This table is taken from Amenc, Goltz, and Sivasubramanian (2016).

	USA Long Term Track Records (Dec 1973 to Dec 2013)	Max Deconcentration	Div. Risk Weighted	Max Decorrelation	Efficient Minimum Volatility	Efficient Maximum Sharpe Ratio	Cap-Weighted
Before Turnover Control	Annualised return	13.82%	13.77%	13.75%	13.61%	13.74%	10.95%
	Annualised volatility	17.46%	16.65%	16.83%	14.30%	15.96%	17.38%
	Ann. 1-Way turnover	23.39%	25.35%	58.84%	54.78%	64.71%	2.67%
	Annualised return net of 20bps transaction costs	13.78%	13.72%	13.63%	13.50%	13.61%	10.95%
	Annualised return net of 100bps transaction costs	13.59%	13.51%	13.16%	13.07%	13.09%	10.92%
	Weighted Average Market Cap (US \$M)	11 237	12 134	10 812	13 239	11 785	47 381
After Turnover Control	Annualised return	13.82%	13.77%	13.83%	13.50%	14.03%	10.95%
	Annualised volatility	17.46%	16.65%	16.74%	14.39%	15.79%	17.38%
	Ann. 1-Way turnover	23.39%	25.35%	36.57%	36.73%	32.35%	2.67%
	Annualised return net of 20bps transaction costs	13.78%	13.72%	13.76%	13.42%	13.97%	10.95%
	Annualised return net of 100bps transaction costs	13.59%	13.51%	13.46%	13.13%	13.71%	10.92%
	Weighted Average Market Cap (US \$M)	11 237	12 134	10 908	13 271	11 794	47 381

## 6) The Turnover Critique: "Smart Beta necessarily leads to high turnover"

Ratio strategy is 13.71% in the presence of turnover controls as opposed to 13.09% in their absence.

These results strongly suggest that post-optimisation optimal turnover control need not significantly alter the benefits of alternative weighting schemes over the long run, but does bring down turnover and thus implementation costs substantially.

### Conclusions

It is clear from the mechanics of Smart Beta strategies that such strategies will tend to display higher turnover than simple cap-weighted portfolios. However, whether or not such strategies lead to excessive turnover is a question of how they are implemented. An illustrative example shows that strategies that may lead to high turnover when tested in abstraction from implementation concerns may be brought to achieve moderate levels of turnover when turnover control methods are employed. It is remarkable that, in the illustrations cited here, such turnover-controlled strategies show little alteration in risk and return properties. These turnover control methods do not significantly impact gross outperformance. It follows that if once trading costs are accounted for, it is clear that turnover rules offer significant net performance benefits.

These results are in line with recent research (Novy Marx and Velikov (2016)<sup>96</sup>) which shows that factor investment strategies which are commonly analysed in academic research may have relatively high levels of turnover, but that transaction cost mitigation strategies can be implemented that leave these strategies profitable<sup>97</sup>.

Overall, it thus appears that, while Smart Beta strategies will necessarily incur higher turnover than cap-weighted market indices, there are well known techniques to keep turnover within reasonable bounds while maintaining the outperformance potential. Investors should thus analyse the turnover mitigation aspects of these strategies and request transparency on incurred turnover from providers. Indeed, an investor's serious analysis of the turnover aspects of a specific strategy that may be of interest in a given investment context seems more appropriate than reliance on blanked or biased criticism of Smart Beta.

96 - Novy-Marx, R. and M. Velikov. 2016. A Taxonomy of Anomalies and Their Trading Costs, *Review of Financial Studies* 29(1): 104-147.

97 - The authors study a wide range of anomalies beyond the most consensual factors and find that " Most of the anomalies (...) with one-sided monthly turnover lower than 50% continue to generate statistically significant spreads after accounting for transaction costs, at least when designed to mitigate transaction costs. Few of the strategies with higher turnover do."

## 7) The Crowding Hypothesis: "If everyone knows about Smart Beta the benefits will disappear"

### Overview – Assessing crowding risk requires research, not just anecdotes

Smart Beta has been establishing a space in between traditional (cap-weighted) passive investments and traditional (proprietary and discretionary) active management. Smart Beta draws fierce criticism from providers of both traditional active management and traditional passive management. Perhaps unsurprisingly, advocates of traditional active and passive management find that Smart Beta is not quite to their liking. In nutshell, proponents of proprietary active strategies complain that Smart Beta is not active enough (see for example Yasenchak and Whitman (2015))<sup>98</sup> while proponents of traditional cap-weighting say that Smart Beta is not passive enough (see for example Philips et al. (2015))<sup>99</sup>.

Among such critiques, a recurring issue is the presumption of a risk of "crowding" in Smart Beta strategies. While crowding is commonly pointed to as a potential risk, it is rarely formalised or even defined. This absence of definition is an issue when none wants to draw founded conclusions. Indeed, if it is now clear how crowding is defined or how it can be measured, it is rather futile to talk about whether or not it has or will occur.

The main idea behind a crowding risk is that, as everyone knows about successful Smart Beta strategies and increasingly invests in them, flows into these strategies will ultimately cancel out their benefits. If an increasing amount of money starts chasing the returns to a momentum strategy for example, it is possible that the reward for holding this strategy – which has been documented with historical data – will ultimately disappear.

Given that the most popular Smart Beta strategies already have a wide following,

it should be feasible to establish evidence of the negative effects, if they exist, of being followed by increasing numbers of investors. It should be feasible to analyse whether popular Smart Beta indices have led to over-crowding and come up with an empirical estimate of the magnitude of the drag associated with crowding that has occurred so far. As of today and to the best of our knowledge, there is no such evidence. This of course does not mean that such evidence may not be produced in the future, but it is important to ask what current claims about crowding are founded upon and the answer is often that we are in the sphere of unfounded assertions.

Moreover, even when looking at the reasoning behind the supposed risk of crowding, one discovers several issues with the common wisdom about crowding.

Below, we first address the insights one can gain from considering the economic rationale of factor premia. We then turn to reviewing the empirical evidence on crowding and finally discussing practical considerations.

### Crowding risk and economic explanations of factor premia

Whether or not we should expect crowding in Smart Beta strategies is closely related to the economic explanations of the premia we observe in the data. If factor premia are explained by a rational risk premium, the factor premium is likely to persist, because some investors will rationally avoid a tilt despite the higher returns. Some investors may rationally choose to accept the lower returns of stocks that have good payoffs in bad times where marginal utility of consumption is high, and may thus hold portfolios that go against rewarded factor tilts (e.g. by focusing on large cap

98 – Yasenchak, R., and P. Whitman. 2015. Understanding the Risks of Smart Beta, and the Need for Smart Alpha. Intech Janus White Paper, available at: <http://ow.ly/WEKQ2>.

99 – Philips, C., D. Bennyhoff, F. Kinniry, T. Schlanger, and P. Chin. 2015. An Evaluation of Smart Beta and other Rules-based Active Strategies. Vanguard White Paper, Available at: <http://ow.ly/WELkv>.

## 7) The Crowding Hypothesis: "If everyone knows about Smart Beta the benefits will disappear"

growth stocks). If on the contrary, factor premia are due to systematic errors, and investors learn over time to correct these errors, factor strategies may indeed see diminishing premia, except if there are limits to arbitrage which mean that many investors will not be able to benefit from the premium. This issue has been discussed extensively in, e.g. Cochrane (1999)<sup>100</sup>. Proponents of the crowding argument claim that crowding will occur in standard factors and factor premia will diminish, but this is not to be expected factors are explained rationally. More specifically, section 2 of this paper discussed explanations that are available in the literature for why factor premia may exist on standard factors. Such economic explanations provide reasons for why factor premia should persist, even if investors are widely aware of them. Some investors will shy away from exploiting the premium even if they are convinced of its existence, simply because they are not willing to take the associated risks, or because they are prevented from going against biased behaviour because of institutional constraints.

Some who theorise about the existence of crowding argue that the losses occurring in a particular factor at some point in time are evidence of "crowding". For example, Yasenchak and Whitman (2015) argue that "given the increase in popularity of smart-beta strategies, there is a similarly increased overcrowding risk, which could result in factor crashes."

Given such claims, one can ask whether the losses in a particular factor at a particular point in time are indeed evidence of crowding. Indeed, if a loss in a factor is proof of "crowding" one might as well claim that, if the equity market factor has experienced crashes, there must be overcrowding in the cap-weighted equity

index. And when long-term bonds severely underperform short-term bonds over a short period, is this then evidence of crowding by investors who are chasing the term premium? How can we conclude that such fluctuations are due to "crowding" rather than normal price fluctuations associated expected for risky assets that are completely "uncrowded"? Again, in the absence of a definition of crowding, it is not clear what one can conclude. If the argument is simply that returns vary over time and at times may be low, then it is not clear how factors are any different from e.g. the equity market. And the fact that returns vary over time does not mean that, in practice, investors are better off by accounting for such time variation through "timing" decisions rather than being exposed to the long-term premium (see Asness (2016))<sup>101</sup>.

In fact, claiming that there must be crowding in a factor because it suffers from losses completely ignores the nature of risk premia. A risk premium corresponds to a higher average return that is due to taking on additional risk. All risk factors will have returns which vary substantially over time, and only an analysis of long-term data can lead to any meaningful conclusions on the average premium. We should note with Black (1993)<sup>102</sup> that "we need decades of data for accurate estimates of average expected return. We need such a long period to estimate the average that we have little hope of seeing changes in expected returns." An example of the difficulties in concluding on changes of factor premia is the small cap effect.

There is a widely held belief that the size effect has disappeared after it has been widely published. This is however mainly based on empirical results over the period 1980 to 2000 and thus sample-specific.

100 - Cochrane, J. 1999. Portfolio Advice for a Multifactor World. *Economic Perspectives* - Federal Reserve Bank of Chicago 23(3): 59-78.

101 - Asness, C. 2016. The Siren Song of Factor Timing, *Journal of Portfolio Management* (forthcoming).

102 - Black, F. 1993. Estimating Expected Return. *Financial Analysts Journal* 49(5): 36-38.

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For example, Schwert (2003)<sup>103</sup> states that "it seems that the small-firm anomaly has disappeared since the initial publication of the papers that discovered it" and Hirshleifer (2001)<sup>104</sup> states that "the U.S. small firm effect has been weak or absent in the last 15 years." However, over the long term, Fama French (2015c)<sup>105</sup> show that the size factor is empirically important whether it is for the period 1927-1963 or 1963-2013.

To illustrate that conclusions on disappearance of the small cap premium can be sample specific, below we show the size premium (annualised return) and its associated t-statistic over rolling periods of 15 years.

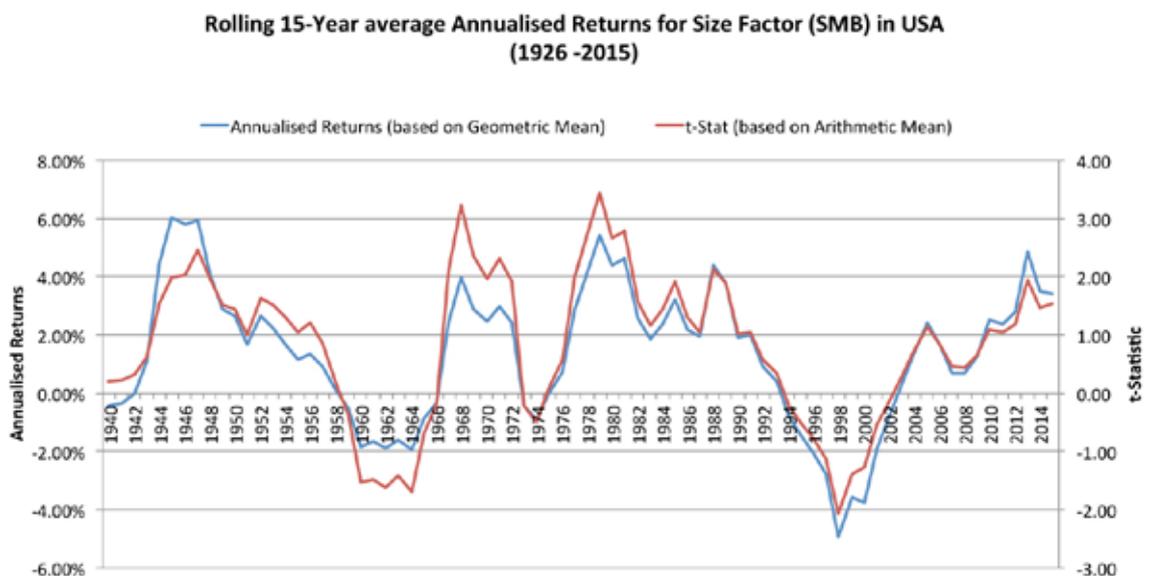
The results in Exhibit 5 suggest that, at times, one will tend to conclude that the premium has disappeared when looking at such time periods of 15 years. However, the widely popularised belief that the size premium has disappeared is not found in the most recent data. Moreover, while the size premium was lower during the

15 years after the publication of the seminal paper by Banz in (1981)<sup>106</sup>, the premium had also been low or negative in earlier times, such as the early 1960s. Therefore, the conclusion that the size premium has disappeared because of the wide publication of this phenomenon is not obvious from such empirical results. Perhaps such results merely suggest that returns to factors vary over time and we need very long time spans of data to conclude on the significance of a premium.

Even over relatively long time spans it is difficult to conclude reliably that a factor has truly disappeared, given the variation in premia. A fortiori, claiming that factor premia have disappeared due to crowding based on short-term events is a risky business as far as the reliability of such conclusions is concerned.

Indeed, due to fluctuations in average returns, it is expected that we will observe periods with low returns, and given the uncertainty in estimating returns reliably,

Exhibit 15: Rolling 15-year average annualised return premium of Size Factor USA Size (SMB) Factor returns are obtained from Kenneth R. French's data library [http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data\\_library.html](http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). The analysis is based on daily returns from 01/07/1926 to 31/12/2015 Starting from 1926 15 year average annual returns are calculated by rolling each year forward till 2015 and the corresponding t-statistics are calculated.



103 - Schwert, G.W. 2003. Anomalies and market efficiency. *Handbook of the Economics of Finance* 1: 939-974.

104 - Hirshleifer, D., 2001. Investor Psychology and Asset Pricing. *The Journal of Finance* 56(4): 1533-1597.

105 - Fama, E. F. and K. R. French. 2015. Incremental variables and the investment opportunity set. *Journal of Financial Economics* 117(3): 470-488.

106 - Banz, R. W. 1981. The Relationship between Return and Market Value of Common Stocks. *Journal of Financial Economics* 9(1): 3-18.

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any sample-specific conclusions should be handled with care. As an example, it is noteworthy that while the size factor is often claimed to have disappeared, and the value factor has been argued to be redundant based on sample-specific analysis, more general findings typically conclude that such factors are still relevant. For example, Fama and French (2015a)<sup>107</sup> concluded based on a US sample that the value factor is redundant but Fama and French (2015b)<sup>108</sup> do not find evidence of the redundancy of the value factor in global data and caution that their earlier results on redundancy may be sample-specific. Moreover, comprehensive comparisons of multi-factor models including different sets of factors show that factors such as value and size need to be included to successfully explain the cross-section of expected returns (see Barillas and Shanken (2015))<sup>109</sup>.

In a nutshell, focusing on specific time periods is ill-suited to drawing inferences on the long-term behaviour of factors. In fact, losses to any factor strategy over any particular period do not necessarily suggest that the long-term premium has disappeared because of "crowding" into a fashionable factor. Such losses may simply suggest that the reward for holding the factor comes with associated risk.

### Where is the evidence?

While there is no specific evidence on the crowding effects in particular Smart Beta indices, a small number of recent studies examine potential effects of wide use of common factors for which a reward has been broadly documented.

While proponents sometimes cite such studies to substantiate their claims about crowding risk, it should be emphasized

that recent studies do not provide clear evidence to suggest that factor premia are likely to disappear because of crowding.

When inspecting the results in the unpublished working paper of Yost Bremm (2014)<sup>110</sup> which is sometimes cited in support of the crowding theory, one does not find conclusive evidence that crowding effects impose any meaningful cost on factor investors. Even though the paper finds evidence of abnormal trading volume for stocks which switch across thresholds of standard factor portfolios, the results do not necessarily imply a heavy burden or cost to strategies following standard factors. In fact, the evidence presented is strong for effects on trading volume but much weaker for effects on stock returns.

In fact, if one considers for example the effects around stocks that switch into the value portfolio, the results suggest the following. The study reports an effect on trading volume which is significant and consistent. Volume in switching stocks tends to increase consistently and in a statistically significant manner across the different model specifications the author tests. However, the return effect is not very consistent. Thus, while the volume effects are consistently shown as positive and significant for stocks switching to the value portfolio, return effects are often insignificantly different from zero across the different model specifications, which is hardly strong evidence of an abnormal return phenomenon. Moreover, results in the paper show that a small percentage of firms actually switch into the value portfolio so that any abnormal returns of switching stocks only apply to a small fraction of assets held. The overall effect on a value portfolio investor would be muted by the fact that most of the assets held are not switching stocks.

107 - Fama, E. F., and K. R. French. 2015a. A Five-Factor Asset Pricing Model. *Journal of Financial Economics* 116(1): 1-22.

108 - Fama, E., and K. French. 2015b. International Tests of a Five-Factor Asset Pricing Model. Working paper, available at: <http://ssrn.com/abstract=2622782>.

109 - Barillas, F., and J. Shanken. 2015. Comparing Asset Pricing Models. Working paper, available at: <http://ssrn.com/abstract=2676709>.

110 - Yost-Bremm, C. 2014. Abnormal Trading Around Common Factor Pricing Models. Working paper.

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McLean and Pontiff (2016)<sup>111</sup> address the question of whether the publication of results showing a return premium associated with an equity factor destroys this premium going forward. Specifically, they analyse the returns to almost 100 different strategies that tilt towards single or composite variables, such as accounting variables or return-based variables. It should be noted that the study includes both consensual factors, such as those listed in the table above, and less standard factors. Such non-standard factors are based on variables such as the firm age, corporate governance measures, inventory-related measures, seasonality, revenue surprises, changes in R&D spending, and analyst earnings forecasts<sup>112</sup>. The authors analyse the in-sample result for a return premium over the period used in the original study. They contrast this premium with the premium observed out of sample but before publication, and with the post-publication premium up to today.

If investors automatically "crowd" into factors once they know about the documented reward, one would expect the premia to decline after publication of the respective paper. McLean and Pontiff attribute a 32% drop in returns to the publication effect. However, the authors also reject the hypothesis that post-publication anomaly returns decay entirely. The key conclusion is thus that while the publication of academic research tends to lower returns going forward, these premia do not disappear. It is noteworthy that this result is obtained when analysing a large number of almost 100 factors, which include not only standard factors. As one increases the number of factors it may indeed be plausible that this may include ad-hoc factors with no clear economic rationale. Persistence of premia may arguably be even stronger when constraining the

analysis to factors with a strong risk-based explanation. That the authors reject the hypothesis of disappearing rewards even for an extensive set of factors which may include strategies that do not have a strong risk-based rationale is indeed strong evidence against the theory that crowding automatically cancels out factor returns for any systematic Smart Beta strategies.

### Conclusion - A practical answer to crowding concerns

While there is no convincing evidence to prove the crowding theorists correct, thinking about the economic rationale behind a specific premium should provide ample answers to crowding concerns. If a factor return is explained by a risk-based rationale, there is no reason to expect crowding. For example, one may theorise that the well-documented long-term outperformance of equity index funds or long-term bonds over money market funds leads to crowding in the higher return funds. However, if such extra return is compensation for additional risk (i.e. the equity premium and the term spread), there is no reason why such premia should disappear even if they are known to investors. Therefore, potential Smart Beta investors should conduct thorough due diligence, not only on the past performance of a given strategy, but also on its economic rationale, and question whether a given reward can be expected to persist.

Moreover, precautions against crowding risks can be taken by proper implementation of factor investing and Smart Beta indices. In particular, the best precaution against crowding seems to be diversification. If investors spread their Smart Beta investments across several strategies, and several factors, there should

<sup>111</sup> - McLean, R. D. and Pontiff, J. 2016. Does Academic Research Destroy Stock Return Predictability? *Journal of Finance* 71(1): 5-32.

<sup>112</sup> - These variables are listed in the internet appendix to McLean and Pontiff (2016), see Table I.A.III.

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not be crowding in a single strategy. Put differently, with so many different implementations across providers it is hard to imagine how crowding in a particular strategy would occur. Moreover, if any standalone strategy is well-diversified with weights spread out over a large number of stocks, such strategies should be less prone to potential crowding. Crowding concerns thus reinforces the arguments on the importance of diversification discussed in section 3.

Of course, it is possible that Smart Beta and factor strategies can be subject to adverse effects due to a wide following but one can only conclude that this is the case if there is evidence for it. Simply referring to losses in a given strategy however is not an evidence of crowding. Moreover, if one is concerned about potential crowding, the immediate concern should be to i) hold well-diversified rather than concentrated strategies, and ii) spread out over many different strategies. Such an approach of avoiding concentration and diversifying across strategies is easy to implement with Smart Beta indices, given the multitude of offerings available, and the different methodological choices across different indices. In addition, the concerns over “crowding” issues underline the importance of clarifying investment beliefs and understanding the rationale for a given factor premium. One can refer to Cochrane (1999) and Ang et al. (2009)<sup>113</sup> who discuss the practical implications of academic findings in asset pricing for portfolio management. Such findings suggest that if risk adverse investors are willing to accept lower returns for holding assets that tend to generate relatively high payoffs in times when marginal utility is high, they provide supply for other investors who are seeking to increase returns through exposure to such risk factors.

The confusion about factor crowding can have negative consequences for investors. Such confusion may lead investors to invest in novel exotic factors which in the end are not rewarded and expose investors to heightened data-mining risks. In fact, exotic new factors are typically justified on short-term data and use proprietary complex scoring approaches to claim that such factors are less replicable and therefore less prone to crowding but a necessary consequence is that these factors are often over-fitted and result from model mining and will not be robust out of sample. Confusion about crowding can also help to promote false ideas about the timing capacity of fundamentally weighted approaches or their capacity to identify underpriced stocks which has nothing to do with evidence based investing through factors but much to do with ad hoc storytelling approaches and with a low tech and probably low efficiency approach to active management.

113 - Ang, A., W. N. Goetzmann, and S. M. Schafer. 2009. Evaluation of Active Management of the Norwegian Government Pension Fund – Global. Research paper (December), see page 24-25 in particular.

# Part 3: Strategy Design Choices

## 8) The Concentration Fallacy: "A good factor index should provide a strong tilt to the desired factor"

### Overview of the Claim

Concentrated factor indices aim to produce strong tilts towards factors by identifying stocks with pronounced factor scores and concentrating into these stocks by either capitalisation-weighting restrictive stock selections or applying to the universe or a restrictive selection a weighting scheme that promotes concentration into the stocks with the highest scores (for example score-based weighting or score-adjusted capitalisation weighting). These approaches result in highly concentrated indices with low effective number of stocks. The objective of such approaches is to establish the strongest exposure possible to the targeted risk factor and, in the context of long-term rewarded risk factors, to try and maximise long-term returns.

Providers commonly argue that the strength of the tilt is a reasonable objective for a factor index. An index provider may write that its factor indices are<sup>114</sup> "designed to produce *strong factor exposure* by weighting the individual stocks by factor signal" or an asset manager that<sup>115</sup> "an index must have a *strong tilt* toward the compensated risk factor" to produce "superior risk-adjusted returns."

We analyse this idea by contrasting approaches building concentrated indices aimed at strong tilts with approaches that instead aim at obtaining well-diversified factor tilted indices.

### Smart Factor Indices

An alternative to concentrated indices exists in the form of well-diversified indices. In particular, Smart Factor Indices<sup>116</sup> do not focus on achieving strong factor exposure through concentration but rather combine

reasonable factor exposure and strong diversification. In particular, these indices implement an explicit factor-based stock selection to obtain the desired tilt as a first construction step and, in a second step, apply a diversification-based weighting scheme to the selection so as to dispose of stock-level idiosyncratic risk. The idea behind this approach is to reconcile the exposure to the right systematic factor with avoidance of (unrewarded) idiosyncratic risk arising from excessive portfolio concentration; further risk reduction can be achieved by combining several diversification strategies to dispose of weighting-scheme level idiosyncratic risk. Poor portfolio diversification exposes the investment to risks of excessive volatility over the short and medium term.

Our recent research<sup>117</sup> has compared the results of such well-diversified factor indices with examples of concentrated factor indices. Before turning to the empirical comparison, a number of conceptual considerations are in order.

### Conceptual Issues

Products that aim to capture explicit risk-factor tilts through concentrated portfolios effectively neglect adequate diversification. This is a serious issue because diversification has been described as the only "free lunch" in finance. Diversification allows a given exposure to be captured with the lowest level of total risk required as it eliminates non-systematic risk. In contrast, taking on factor exposures exposes investors to systematic risk factors. Rewards for doing so do not constitute a "free lunch" but compensation for risk in the form of systematic factor exposures. Capturing risk premia associated with systematic factors may be attractive for investors who can accept the systematic risk exposure in

114 - <https://www.russell.com/documents/indexes/research/efficient-exposure-to-low-volatility-momentum-quality-and-value.pdf>

115 - <https://www.northerntrust.com/documents/white-papers/asset-management/evaluating-the-efficiency-of-smart-beta-indices-a-new-metric.pdf>

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

117 - See Amenc, N., F. Ducoulombier, F. Goltz, A. Lodh and S. Sivasubramanian. 2016. Diversified or Concentrated Factor Tilts?. *The Journal of Portfolio Management* 42(2): 64-76.

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return for commensurate compensation. However, factor-tilted strategies, when they are very concentrated, may also take on other, non-rewarded, risks. Non-rewarded risks come in the form of idiosyncratic (notably firm-level) risk, as well as other unrewarded risks (e.g. currency risk and other unrewarded micro or macroeconomic factors). Financial theory does not provide any reason why such risk should be rewarded. Therefore, a sensible approach to factor investing should not only look to obtain a factor tilt, but also at achieving proper diversification within that factor tilt. To illustrate this point, we focus on the Value factor as an example below, but the discussion carries over to other factors too.

In fact, if the objective was to obtain the most pronounced Value tilt, for example, the only unleveraged long-only strategy that would achieve this goal would be to hold 100% in a single stock, the one with the largest Value tilt, as measured for example by its estimated sensitivity to the Value factor or its book-to-market ratio. This thought experiment clearly shows that the objective of maximising the strength of a factor tilt is not reasonable. Moreover, this extreme case of a strong factor tilt highlights the potential issues with highly concentrated factor indices.

Even if the appropriateness of such an extreme approach had been established, any Value premium so captured would necessarily come with a large amount of idiosyncratic risk. This risk is not rewarded and therefore we should not be expecting the strategy to lead to an attractive risk-adjusted return. Additionally, it is unlikely that the same stock will persistently have the highest Value exposure within a given investment universe. Therefore, a periodically-rebalanced factor index with

such an extreme level of concentration will likely to generate 100% one-way turnover at each rebalancing date, as the stock that the strategy held previously is replaced with a new stock that displays the highest Value exposure at the rebalancing date. While practical implementations of concentrated factor-tilted indices will be less extreme than this example, we can expect problems with high levels of both idiosyncratic risk and turnover whenever index construction focuses too much on concentration and pays too little attention to diversification.

Interestingly, Benjamin Graham himself underlined the importance of diversification for a given factor tilt many decades ago. As noted by Asness et al.(2015)<sup>118</sup>, the 1973 edition of Graham's famous book on value investing reads: "In the investor's list of common stocks there are bound to be some that prove disappointing... But the diversified list itself, based on the above principles of selection [...] should perform well enough across the years. At least, long experience tells us so." Aiming at a highly-concentrated value portfolio would be completely inconsistent not only with financial theory, but also with the principles put forth by the early advocates of value investing.

When constructing portfolios including a broad selection of value stocks, cap-weighted portfolios of such stock selections may at first seem to be a more neutral implementation than equal-weighted portfolios. However, it is well known that cap-weighting has a tendency to lead to very high concentration given the heavy-tailed nature of the distribution of market cap across. It is well documented in the academic literature that simple cap-weighted, Value-tilted portfolios have not led to attractive performance. In fact

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across different studies on equity risk factors, Fama and French emphasised the need for a well-diversified portfolio as a proxy for a factor tilt. For example, Fama and French (2012)<sup>119</sup> wrote that they "ensure that [they] have lots of stocks in each [factor-tilted] portfolio" and argue that factor-tilted portfolios should be well-diversified in order to obtain factor tilts which are reliable in the sense that factor exposures can be estimated with precision.

The need for diversification is explicitly recognised by Hou, Xue and Zhang (2015)<sup>120</sup> who recall that "value-weighted portfolio returns can be dominated by a few big stocks" (see also Fama and French (2015))<sup>121</sup>. Factor construction reflects this need for diversification. Fama and French (2012) defined the Value factor as "the difference between the returns on diversified portfolios of high book-to-market (value) stocks and low book-to-

market (growth) stocks." The fact that the most widely cited researchers documenting the relevance of the value factor do not use simple cap-weighted factors, but rather construct more balanced portfolios, shows the lack of support for industry practices using simple cap-weighted factor indices.

Overall, it thus appears that neither of the approaches that propose to construct concentrated factor indices is supported neither by the academic literature nor by common sense.

### Detailed Comparison of Concentrated and Diversified Factor-Tilted Portfolios

In this section, we compare portfolios for six factor tilts, each with different stock selection filters, which are constructed using two different weighting schemes – cap weighting (CW) and equal weighting

*Exhibit 16: Performance of Cap Weighted and Equal Weighted Factor Indices - The time period of analysis is 31-Dec-1974 to 31-Dec-2014 (40 years). All figures reported are average figures across six factors – size, momentum, low volatility, value, low investment, and high profitability. All factor-tilted portfolios are rebalanced annually on the third Friday of June except for Momentum tilted portfolios, which are rebalanced semi-annually. The analysis is done using weekly total returns (dividends reinvested) in USD. The portfolios are constructed using a US stock universe that contains the 500 largest stocks by total market capitalisation. The market-cap-weighted index of these 500 stocks is the benchmark. The yield on secondary market US Treasury Bills (3M) is the risk-free rate. All risk and return statistics are annualised and the Sharpe and information ratios are computed using annualised figures. The outperformance probability (3 years) is the probability of obtaining positive relative returns if one invests in the strategy for a period of 3 years at any point during the history of the strategy. It is computed using a rolling window of length 3 years and a 1-week step size. The average relative returns in positive (negative) periods are the mean of only positive (negative) rolling 3-year annualised relative returns. The extreme relative returns in positive (negative) periods are the 95th (5th) percentile of only positive (negative) rolling 3-year annualised relative returns. Data sources: CRSP and WRDS. Table taken from Amenc, Ducoilombier, Goltz, Lodh and Sivasubramanian (2016).*

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

119 - Fama, E. F. and K. R. French. 2012. Size, Value and Momentum in International Stock Returns. *Journal of Financial Economics* 105(3): 457-472.

120 - Hou, K., C. Xue and L. Zhang. 2015. Digesting Anomalies: An Investment Approach. *Review of Financial Studies* 28(3): 650-705.

121 - Fama, E.F. and K. R. French. 2015. A Five-Factor Asset Pricing Model. *Journal of Financial Economics* 116(1): 1-22.

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(EW). Two grades of filters are used; the broad filtering selects the top 50% stocks, in terms of factor scores, from the stock universe at each rebalancing and the narrow filtering selects the top 20% stocks. The exhibit below shows a detailed comparison between concentrated (CW) portfolios and more diversified (EW) portfolios. In the long run, on average, across the six factor tilts, the performance and risk-adjusted performance of the concentrated portfolios is inferior to that of the diversified portfolios both for the broad and the narrow selections. With the broad selection, the average Sharpe ratio goes up from 0.55 to 0.66 when one moves from concentrated to a diversified portfolio. Similarly with the narrow stock selection, the Sharpe ratio rises from 0.58 to 0.67.

Applying a diversification scheme, without any doubt, increases the tracking error with respect to the broad cap-weighted benchmark. But the risk-adjusted out-performance or information ratio remains higher for the diversified factor-tilted portfolios. For example, for the broad selection case, on average across the 6 factors, the information ratio of diversified factor-tilted portfolios is twice that of their concentrated counterparts (0.66 vs. 0.33) for CW factor-tilted portfolios.

Increasing factor concentration by shifting to the narrow selection does not have a meaningful impact on risk-adjusted returns. For a given weighting scheme, increasing concentration through a more focused stock selection has a marginal positive impact on the average Sharpe ratio. On average across weighting schemes, the information ratio falls when moving from the broad to the narrow selection. Thus there is no added value, from a risk-adjusted performance perspective, in

having factor-tilted portfolios that are more concentrated. Also note that, both in terms of gross performance and risk-adjusted performance, it is significantly better to diversify a broad selection than to narrow the selection while keeping capitalisation-weighting.

The exhibit above showed that for the same level of total risk, measured by portfolio volatility, the concentrated factor-tilted portfolios posted lower returns than their diversified counterparts. This indicates that a lot of the risk taken by capitalisation-weighted portfolios must be unrewarded or idiosyncratic in nature.

To verify this conjecture, we analyse the idiosyncratic risk of concentrated and diversified factor portfolios to show that the previous results are consistent with portfolio theory, i.e. that more concentration leads to more idiosyncratic risk, which is unrewarded.

In order to strip out the systematic component of portfolio risk, we use a Carhart four-factor regression model (Carhart (1997)<sup>122</sup>). The next exhibit shows that, irrespective of the weighting scheme chosen, the residual risk is larger in the case of narrow stock selection. The average standard deviation of regression residuals increases upon moving from broad to narrow stock selections; from 0.51% to 0.82% with capitalisation weighting, and from 0.61% to 0.79% with equal weighting. The inter-quartile range of the residuals is also higher in the case of narrow stock-selection portfolios, which shows that the portfolio's idiosyncratic risk increases as the number of stocks falls. It should be noted that evaluating performance and risk using a factor model which includes a Size factor, as in the case of the Carhart model, allows the possible small/mid cap exposure

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of the respective indices to be taken into account. Indeed, to improve diversification, it is necessary to deconcentrate away from the largest capitalisations in which capitalisation-weighting approaches and better the balance of constituent weights. The Carhart four-factor model takes into account returns for Market, Size, Value and Momentum exposures to produce an excess return figure that is net of these systematic influences.

Annualised alpha per unit of residual standard deviation, which is a measure of unexplained performance adjusted by idiosyncratic risk, increases on average from 1.24 for broad-selection concentrated portfolios to 2.34 for their diversified counterparts – the figure increases from 1.30 to 1.92 with the narrow selections.

The next exhibit shows that switching from concentrated to diversified weighting scheme for broad-selection factor-tilted portfolios brings fewer implementation challenges than switching to a narrower stock selection while remaining cap-weighted. On average, turnover does not show any considerable increase when moving to the diversification weighting scheme: the average turnover rises some 11% (from 29.25% to 32.58%). On the other hand, switching to the narrow-selection while remaining cap-weighted produces an average increase in turnover that is close to 1.6 times larger (as turnover jumps to 48.15%). Meanwhile, diversifying a broad selection or narrowing the selection while remaining cap-weighted result in comparable changes in liquidity as measured by the time required to trade.

*Exhibit 17: Diversification Effects in Cap-Weighted and Equal-Weighted Factor Indices - The time period of analysis is 31-Dec-1974 to 31-Dec-2014 (40 years). All figures reported are average figures across six factors – size, momentum, low volatility, value, low investment, and high profitability. All factor-tilted portfolios are rebalanced annually on the 3rd Friday of June except for Momentum tilted portfolios, which are rebalanced semi-annually. The analysis is done using weekly total returns (dividends reinvested) in USD. The portfolios are constructed using a US stock universe that contains the 500 largest stocks by total market capitalisation. The market-cap-weighted index of these 500 stocks is the benchmark. The yield on secondary market US Treasury Bills (3M) is the risk-free rate. A Carhart 4-factor model is used for regression analyses. The reported alpha is annualised. The market factor is the excess returns of the cap-weighted benchmark over the risk-free rate. The size, value, and momentum factors are obtained from Kenneth French's data library. More details available in Amenc, Ducoulombier, Goltz, Lodh and Sivasubramanian (2016). Data sources: CRSP and WRDS.*

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

*Exhibit 18: Implementation of Cap-Weighted and Equal-Weighted Factor Indices - All figures reported are average figures across six factors – size, momentum, low volatility, value, low investment, and high profitability. All factor-tilted portfolios are rebalanced annually on the 3rd Friday of June except for Momentum tilted portfolios, which are rebalanced semi-annually. The analysis is done using weekly total returns (dividends reinvested) in USD. The portfolios are constructed using a US stock universe that contains the 500 largest stocks by total market capitalisation. The market-cap-weighted index of these 500 stocks is the benchmark. The reported Turnover is Annual 1-Way Turnover and is averaged over 40 annual rebalancings in the period 31-Dec-1974 to 31-Dec-2014. Days to Trade or DTT of a stock is the number of days required to trade total stock position in the portfolio of \$1 billion, assuming that 10% of 'Average Daily Traded Volume (ADTV)' can be traded every day. For each portfolio, the reported DTT value is the 95th percentile of DTT values across all 10 yearly rebalancings in the period 31-Dec-2004 to 31-Dec-2014 and across all stocks. Table taken from Amenc, Ducoulombier, Goltz, Lodh and Sivasubramanian (2016). Data sources: CRSP and WRDS.*

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

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### Conclusion

Factor indices are a potentially value-adding tool. Investors can expect benefits from relying on indices which tilt towards well-documented factors that offer sizeable and repeatable return benefits over long investment horizons. However, when aiming to implement the insights from empirical asset pricing, one should remember a more fundamental insight from financial theory, i.e. that diversifiable risk commands no premium. Our results suggest that index construction approaches which build diversified portfolios for a given factor-based stock selection are exposed to less unrewarded risk and outperform their concentrated counterparts. Considering these two aspects, namely factor tilts and diversification, should be an integral part of a sensible factor index design methodology.

Moreover, factor indices are indices after all, and thus should be implementable with ease and low turnover. Our results suggest that narrowing stock selections in an effort to improve portfolio-wide factor scores leads to high turnover levels and investability hurdles which are not compensated by significant performance advantages. On the contrary, applying a diversification-based weighting scheme such as equal-weighting to broad stock selections produces significant improvements of performance with only modest increases in turnover. Naturally, equal-weighting can be seen as a starting point for more sophisticated diversification strategies, such as risk-based diversification strategies, which may allow for additional benefits to be obtained.

## 9) The Factor Fishing License: "A good factor index requires a sophisticated scoring approach"

### Overview of the claim

Product providers frequently claim that customisation by innovative factor definitions is the key to Smart Beta strategy design. Indeed, many indices offered by product providers rely on sophisticated proprietary variable definitions to derive factor scores – these may include adjustments of standard metrics, use of alternative metrics, combination of multiple metrics, etc.

The mismatch of the provider definitions with the standard academic definitions is striking. While the Fama and French definitions rely on straightforward variables and make a choice of transparently and simply selecting one key metric to come up with a factor score for each stock, the proprietary definitions from providers use different sets of variables, as well as various adjustments and often consist of complex combinations of variables.

### Issues with non-standard factor definitions

The use of non-standard factor definitions creates a considerable mismatch with the factors that have been independently evaluated over long-term horizons and have stood the test of time and withstood academic scrutiny. The exhibit below shows factor definitions<sup>123</sup> retained in several commercially available factor indices and contrasts them with the Carhart (1997) or Fama and French (2012)<sup>124</sup> factor definitions, which are widely used in academic research that either tests the empirical evidence on these factors or assesses their economic rationales.

For example, some factor scores are calculated relative to the industry or regional group a stock belongs to. Some providers use such industry or region adjustments for certain variables within a given factor score while not using it for other variables making up the same factor score. Moreover, providers often use variables which are quite far removed from the original factor definition. For example, whereas Carhart (1997) and Fama and French (2012) use the readily observable one-year price appreciation (excluding the last month on the basis of the work of Jegadeesh and Titman (1993)<sup>125</sup>) as their definition of Momentum, MSCI combines two technical analysis momentum

Exhibit 19: Mismatch with academic factor definitions: Examples

Provider	Value	Momentum
Carhart (1997) and Fama-French (2012)	Price to Book	Past 12 Months return (omitting last month)
Goldman Sachs Equity Factor Index World	Value score from proprietary risk model (Axioma), relative to stock's regional industry group	Residuals from cross sectional regression of twelve month return (omitting last month) on stock volatility
MSCI Diversified Multi Factor Indices	Sector-relative composite based on Enterprise Value / Operating Cash Flows, Forward	Composite score based on 12-month relative strength (25% weight), 6-month relative strength (37.5% weight) and historical alpha in a proprietary risk model (GEM2 Barra Equity Model) estimation using 104 weeks of trailing returns.
FTSE Global Factor Index Series	Composite based on cash flow to price, net income to price, and country-relative sales to price	Mean/Standard deviation of "average residual" from 11 rolling window regressions of past 36 months returns on country and industry index
Deutsche Bank Equity Factor Indices	Composite based on inverse of Enterprise Value to EBITDA and dividend yield	Twelve month return (omitting last month) minus risk adjustment times idiosyncratic volatility score

123 - Some details and exceptions in the providers' definitions have been omitted in the interest of conciseness.

124 - Fama, E. F. and K. R. French. 2012. Size, Value and Momentum in International Stock Returns. *Journal of Financial Economics* 105(3): 457-472.

125 - Jegadeesh, N. and S. Titman. 1993. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance* 48(1): 65-91.

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indicators (for periods of six months and one year) with the alpha from a regression of "local excess stock returns against the cap-weighted local excess returns of the GEM2 model estimation universe using 104 weeks of trailing returns."<sup>126</sup> Overall, the different index providers are in stark disagreement with how academic research defines these factors. Instead of using consensual factors, index providers aim at creating "prime" or "enhanced" factors that are intended to outperform standard factor definitions.

### Multiple testing and selection bias

In general, such proprietary definitions increase the amount of flexibility providers have in testing many variations of factors and thus pose a risk of data-mining, and all the more so in that it remains unclear why these adjustments are made and in particular whether there are any fundamental economic reasons for using some of these variables and adjustments for a given factor. In fact, it appears that providers sometimes explicitly aim at selecting ad-hoc factor definitions which have performed well over short-term back-tests. Factor definitions may be selected by back-testing various combinations of variables on a particular dataset spanning a relatively short time period "*on the basis of the most significant t-stat values*" or because they "*display relatively high risk-adjusted performance outcomes*". Today's analytical tools offer easy access to proprietary factors "encompassing millions of back-tests" and allow for selecting those that reflect "the latest practitioner expertise" and are "working currently". It is worth noting that some providers have launched "enhanced" factor indices which replace the factor definitions in their standard factor indices with new

and improved recipes. Such inconsistency of factor definitions over time increases flexibility even further.

Of course, selecting proprietary combinations or making proprietary tweaks to variable definitions offers the possibility to improve the performance of a factor index in a back-test. The question is whether the improvement of the "enhanced" factor definition will also hold going forward, especially if there is no solid economic foundation for it. There is clearly a risk that one ends up with what academics have termed "lucky factors". Harvey and Liu (2015)<sup>127</sup> show that by snooping through data on a large number of candidate factors and retaining those with the highest t-stat, one takes the risk of uncovering flukes, which will not repeat out of sample. Perhaps even more importantly, it is unclear what - if anything - factors with extensive proprietary tweaks still have in common with the factors from academic research. Therefore, the empirical evidence in favour of the academic factors and their economic grounding cannot be transposed to such new proprietary factors.

An early advocate against relying excessively on pure empirical results was the late Fischer Black. Black (1993a)<sup>128</sup> argues that many so-called financial market anomalies "seem likely to be the result of data mining". Black (1993b)<sup>129</sup> reiterates the problem of multiple testing using an anecdote whereby a researcher gives a table filled with t-statistics and the sufficiently big ones are deemed significant at the 5% level - in a situation when only 5% of all the t-statistics presented satisfy the significance criteria. Clearly, in such a sample the 5% of "significant" results are nothing but a result of the confidence level itself - it would be surprising on the

126 - MSCI Diversified Multi-Factor Indexes Methodology, April 2015 at [https://www.msci.com/eqb/methodology/meth\\_docs/MSCI\\_Diversified\\_Multi\\_Factor\\_Indexes\\_Methodology\\_April\\_2015.pdf](https://www.msci.com/eqb/methodology/meth_docs/MSCI_Diversified_Multi_Factor_Indexes_Methodology_April_2015.pdf)

127 - Harvey, C. R. and Y. Liu. 2015. Lucky factors, Working Paper, available at SSRN.

128 - Black, F. 1993a. Beta and return. *The Journal of Portfolio Management* 20(1): 8-18.

129 - Black, F. 1993b. Estimating expected return. *Financial Analysts Journal* 49(5): 36-38.

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other hand, if in large enough sample there would not be 5% of results that are "significant" at the 5% level.

Harvey, Liu and Zhang (2016)<sup>130</sup> investigate the stock of factors that financial research has amassed in the past decades. Their inventory makes out at least 316 factors, most of which have been proposed in the last ten years. Similar to Black (1993a, 1993b) the authors question the validity of the standard t-test thresholds, given multiple testing. They suggest that many of the factors may appear significant purely by chance.

Another warning against the dangers of back-tests is voiced by Bailey and López de Prado (2014)<sup>131</sup>. The authors put into perspective the total amount of data used by today's quantitative analysts by claiming that it is comparable to the memory stored by Netflix to support its video-streaming business. The authors review the problem of multiple testing – as more and more strategies are being tested at the same significance level, the chances of actually including a false positive grow higher and higher. This is because the significance threshold, however small – be it 5%, 1% or even less – is still fixed while the number of trials is not. This is a similar argument to the ones voiced by Harvey, Liu and Zhang (2016) and Black (1993a, 1993b).

The problem of selection bias is ultimately linked to the issue of multiple testing. The authors concede that most of the results that researchers get will ultimately not be published, since publication will be reserved to the results passing the aforementioned significance threshold. Because of this and due to the ever-increasing number of trials, the researcher is ultimately bound to find a "significant" result. The authors

thus recognise that random patterns might be easily mistaken for profitable opportunities in the past data and such random patterns will be the reason why strategies based on in-sample over-fitting will be rendered worthless in live setting. As they put it, the investor selecting the strategy that performed best, among a large number of alternatives, is exposed to a strategy with an inflated Sharpe ratio whose performance out-of-sample will most likely disappoint. They put an emphasis on the fact that running multiple experiments is potentially dangerous and the extent of the trials should be guided by investment theory, thus avoiding the abuse of computational power.

It is important to point out that data snooping bias may not be a consequence of a researcher's or product providers conscious act to perform an analysis sweeping through all the available possibilities. This problem might result as a consequence of more subtle mechanisms. As Black (1993a) notes, data mining problems arise in particular if people build on other's work. Researchers learn from others' mistakes and successes which in turn introduces a subtle survivorship bias, as discussed by Sullivan, Timmerman and White (1999)<sup>132</sup>. The strategies that performed well among thousands of alternatives tend to attract more attention than the ones with poorer historical performance. Work that then expands on those successful strategies, will draw inference based on the subset of surviving strategies which is likely to be misleading. In the same vein, index providers which build their methodologies by responding to client request for popular factor definitions take a risk of picking up a specific subset among potentially thousands of factors that have been tested by hundreds of clients. This subset

130 - Harvey, C. R., Y. Liu and H. Zhu. 2016. ...and the Cross-Section of Expected Returns. *Review of Financial Studies* 29 (1): 5-68.

131 - Bailey, D.H. and M. Lopez de Prado. 2014. The Deflated Sharpe Ratio: Correcting for Selection Bias, Backtest Overfitting and Non-Normality. *Journal of Portfolio Management* 40(5): 94-107.

132 - Sullivan, R., A. Timmermann and H. White. 1999. Data-Snooping, Technical Trading Rule Performance and the Bootstrap. *Journal of Finance* 54(5): 1647-1691.

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of factors corresponds to those back-tests that worked, but given the large number of tests, the benefits may be the result of random variations which are not repeatable out of sample. In a nutshell, by relying on factor definitions that are fashionable with clients, index providers may maximise data-mining bias without actually conducting any data-mining themselves.

### Illustration: Fishing for an Enhanced Value factor

We now turn to a "factor fishing" exercise where we consider alternatives to the standard Value definition. The academic literature works with parsimonious and time-proven definitions of the Value factor, the most popular being the Book-to-Market ratio, due largely to Fama and French (1992). When deviating from the established definitions, one has to keep in mind that these definitions have been confirmed by the out-of-sample results ever since the publications of the seminal papers. This out-of-sample stability gives researchers and practitioners greater confidence that the uncovered value premium is not simply a product of a data-mining exercise.

On the other hand, if we allow ourselves the flexibility of looking for the "best" or "improved" definition of Value, such an exercise can easily lead to relying on promising in-sample results that do not hold out-of-sample.

Commercial back-tests are typically performed on a very short time-frame, in which around ten years of data is frequently used. Since different factor definitions will ultimately lead to different past performance, using a short time period to decide which one to pick might lead to unstable solutions.

Below, we illustrate the problems with variable selection and excessive reliance on back-test with stylised examples. First, we study the change in back-tested performance over time, to see how (un)stable the results of variable selection are. Afterwards, we focus on the out-of-sample decay of performance benefits of in-sample variable selection.

To illustrate the timing problem in back-tests discussed above, we study the rolling spreads between the annualised performances of portfolios constructed based on different Value proxies. This will allow us to get a perspective on how back-tests may have looked like over the years and, more importantly, how the change over time impacted these results.

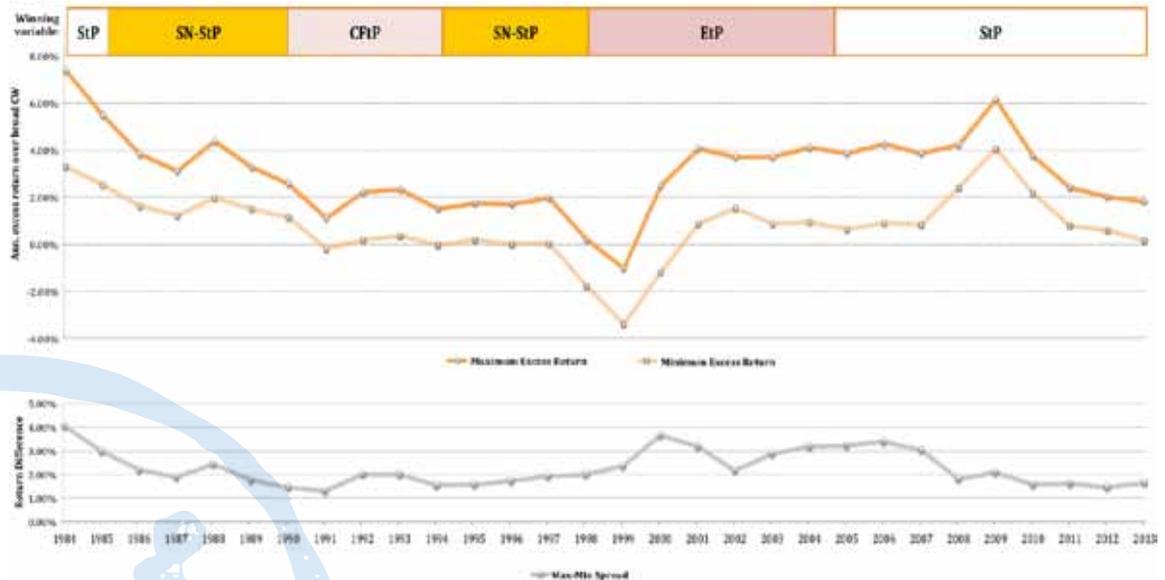
Our question is whether we can do better than using the Book-to-Market measure. We select among ten alternative value metrics - Earnings-to-Price, Cash-flow-to-Price, Sales-to-Price, Dividend-to-Price and Payout-to-Price, using both an unadjusted and a sector-neutral version for each. These metrics serve as the basis for forming a Value-tilted portfolio, where the portfolios simply select the 50 percent of stocks with the highest value score on an annual basis and cap-weight the selected stocks. The time series of these portfolios will serve as the basis for the empirical analysis below.

Consider the following exhibit. Every year, we look ten years back in the history and plot the maximum and minimum annualised relative returns of ten value strategies over the broad cap-weighted index in that particular period. This is done on a rolling basis between 1984 and 2013. Every year thus represents a different potential starting point for a ten-year back-test. Naturally, the excess returns change over time, but one should pay

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Exhibit 20: Extremes of annualised excess returns of ten cap weighted Value strategies for ten year look-back periods

This chart plots the maximum and minimum of annualised excess returns with respect to the broad US market cap weighted benchmark of 500 stocks (from CRSP) of annually rebalanced cap weighted tilted strategies with 50% stock selection out of the universe of 500 US stocks based on 10 Value variables - Earnings-to-Price, Cash-flow-to-Price, Sales-to-Price, Dividend-to-Price and Payout-to-Price, both plain-vanilla and sector neutral versions for each. Ten year trailing returns are obtained with annual step size.



closer attention to the changing spread between the maximum and the minimum.

Over the years, the difference in annualised returns of the possible back-tests ranges from slightly over 4% p.a. to little under 1% p.a. This large spread between the different definitions suggest that considerable Value can be added, at least within a back-test, when improving the variable selection. However, it is also worth noting that the best performing variable changes over time, as the next table shows.

This clearly illustrates that back-tests that search for the best past performer in a short time period might be very unstable and caution should be exercised in evaluating strategies purely constructed on the basis of in-sample performance.

Below, we focus on the performance of strategies based on alternative Value definitions relative to the performance of a portfolio based on Book-to-Market. We know that we can enhance back-tests, but should we? Our illustrations will reveal the out-of-sample decay of the data mined solutions that rely on picking the best in-sample winners.

In the following exercise, we use a five year formation window at the end of which we select the best performing strategy based on its in-sample performance. Then, we hold the strategy for five years and compare the cumulative returns of this alternative strategy with respect to the portfolio based on the Book-to-Market measure. We do this every year between 1984 and 2009 to obtain 26 different

Period	Best performing variable based on 10-year back-test
1984	Sales-to-Price
1985-1989	Sales-to-Price, sector-neutral
1990-1993	Cash-flow-to-Price
1994-1997	Sales-to-Price, sector-neutral
1998-2004	Earnings-to-Price
2005-2013	Sales-to-Price

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event studies and we study the average performance.

The next exhibits shows the average cumulative relative returns of the best performing alternative value definition with respect to Book-to-Market, both pre- and post-formation. As the chart below clearly shows, the average alternative variable definition ultimately underperforms the Book-to-Market and drives the cumulative relative returns way below zero. Picking the past winner yields cumulative outperformance over book-to-market of +1.79% in-sample. However, over the following five years, having picked the in-sample winner leads to cumulative underperformance of -2.72% out-of-sample. This is evidence that searching for a better Value definition in-sample does not beat Book-to-Market.

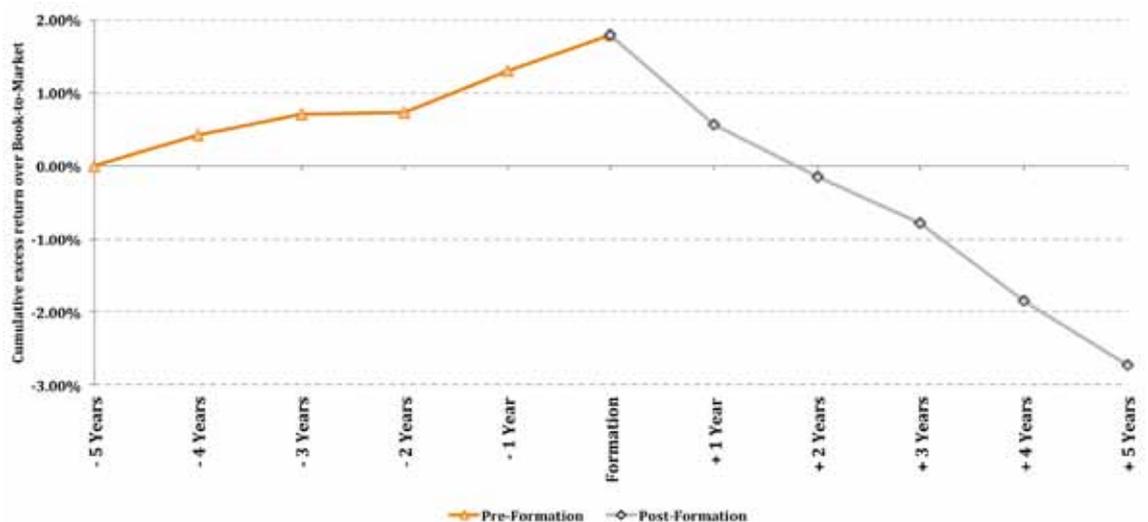
The previous exercise demonstrates that alternative Value definitions hardly present a suitable replacement for Book-to-Market overall, based on the event study approach.

To illustrate this point clearly and more convincingly, we now turn into simulating the experience of an actual investor in alternative Value strategies.

Starting in 1984, we allow the investor to select the best performing Value variable, again using the ten alternative variable definitions specified above. After formation, the portfolio is held for a certain period and re-evaluated again at the end of it. We thus create active strategies that the investor sticks to for the duration of the holding period. We use two lengths of the calibration period (10 and 5 years) as well as four lengths of the holding period (2 to 5 years) for a total of eight active strategies to capture the variability of the performance. We compare the performance of the active strategies based on alternative value definitions with a simple portfolio based on Book-to-Market in the next exhibit. The results clearly show that none of the active strategies beats Book-to-Market, with the average active strategy lagging 61 basis points behind.

*Exhibit 21: Comparison of cumulative relative returns of the average best in-sample alternative Value strategy with respect to portfolio based on Book-to-Market*

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



## 9) The Factor Fishing License: "A good factor index requires a sophisticated scoring approach"

Relative to their in-sample performance, the variable picking strategies on average create an out-of-sample degradation in performance of 128 basis points.

Overall, our empirical illustrations suggest that it is quite possible to enhance back-tests by selecting variables that "work" in sample. However, the strong out-of-sample degradation of performance suggests that such an approach leads to a risk of overstated back-test performance. We emphasise also that we consider our illustration to correspond to a mostly harmless data mining experiment, which is likely to understate the actual bias that could result in more flexible data-mining exercises. In particular, we use a relatively small number of variables that remain economically sensible proxies for value, and which are by construction highly correlated among each other. Data-mining biases would obviously be much higher if we used a much larger number of variables, economically less sensible proxies or variables that are less correlated with each other.

### Over-fitting bias and composite scores

While the selection bias potentially exists for any strategy, there is an additional bias that is specific to so-called composite scoring approaches, factor definitions which draw on combinations of multiple variables. A recent paper by Novy Marx (2015)<sup>133</sup> analyses the bias inherent in back-tests of composite scoring approaches<sup>134</sup>. Novy Marx argues that the use of composite variables in the design and testing of Smart Beta strategies yields a "particular pernicious form of data-snooping bias". He shows that creating a composite variable based on the in-sample performance of single variable strategies generates an over-fitting bias. To make matters worse, this over-fitting bias interacts with the selection bias. The presence of both biases in composite variable Smart Beta strategies increases the data-mining problems exponentially.

Novy Marx analyses the bias occurring in analysis of back-tested performance

Exhibit 22: Performance of Variable Picking Strategies for Value Tilted Portfolios

This table shows the performance of 8 active strategies formed on the basis of calibration period and held for holding period from ten alternative Value definitions. The alternative Value definitions are Earnings-to-Price, Cash-flow-to-Price, Sales-to-Price, Dividend-to-Price and Payout-to-Price, both plain-vanilla and sector neutral versions for each. At formation, the best performing strategy based on the calibration period of 10 or 5 years is selected and held for a holding period of 2 to 5 years. Book-to-Market portfolio is formed annually by cap-weighting the 50% selection of the stocks with the highest Book-to-Market ratio. The in-sample results select the ex-post best returns of the alternative Value strategies. All portfolios are based on the top 500 US stocks between 01/01/1984 and 31/12/2013.

	Book-to-Market	In-sample results			Out-of-sample results of variable picking strategies								
		10 Years	5 Years	Average	Calibration Period = 10 years				Calibration Period = 5 years				Average
					HP=5	HP=4	HP=3	HP=2	HP=5	HP=4	HP=3	HP=2	
Ann. Returns	13.1%	13.7%	13.9%	13.8%	12.7%	12.5%	12.7%	12.6%	12.4%	12.3%	12.3%	12.4%	12.5%
Ann. Volatility	19.0%	18.4%	17.9%	18.1%	18.6%	18.6%	18.6%	18.5%	18.1%	18.6%	18.4%	18.3%	18.5%
Sharpe Ratio	0.47	0.52	0.55	0.53	0.46	0.45	0.46	0.46	0.46	0.44	0.45	0.45	0.45
Ret. Diff with B-t-M	-	0.56%	0.78%	0.67%	-0.37%	-0.60%	-0.43%	-0.46%	-0.69%	-0.80%	-0.77%	-0.75%	-0.61%
Ret. Diff with "in-sample"	-0.67%	-	-	-	-0.93%	-1.17%	-1.00%	-1.03%	-1.47%	-1.58%	-1.55%	-1.53%	-1.28%

133 - Novy-Marx, R. 2015. Backtesting strategies based on multiple signals. Working Paper. National Bureau of Economic Research.

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

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by considering strategies that combine random signals. The results show that combining signals that happened to perform well in the past leads to even better past performance. Given that signals are uninformative by construction, the past performance of these composite strategies of course does not imply any capacity to generate performance out of sample. The author concludes that "combining signals that back-test positively can yield impressive back-tested results, even when none of the signals employed to construct the composite signal has real power".

The analysis also underlines the severity of the overall bias in composite scoring approaches where the selection bias and over-fitting bias interact. Novy-Marx finds that a back-test based on composite scoring using the "best k of n" variables, is almost as biased as a back-test of a strategy where one selects the single variable that had the best performance of  $n^k$  candidate variables. For example, using a composite score where one selects three variables out of six candidate variables is as biased as selecting with hindsight a single variable from 216 ( $6^3$ ) candidate variables. Likewise, selecting a composite of five variables out of ten based on back-tested performance is almost as bad as selecting a single variable among 100,000 ( $10^5$ ) candidate variables. This result underlines that the use of composite scores may lead to severe data-snooping bias. As the author concludes, by "combining spurious, marginal signals, it is easy to generate back-tested performance that looks impressive."

A simple reason for why composite score may be more prone to generating biased results is that a composite variable requires more inputs and thus increases the number of possible choices. There seems to be a wide ranging awareness that composite

strategies, by having more inputs, will lead to increased data mining risk. Pedersen (2015)<sup>135</sup> makes a case against excessive back-testing arguing that "we should discount backtests more if they have more inputs and have been tweaked or optimised more". Likewise, Ilmanen (2013)<sup>136</sup> states that analysis involving "tweaks in indicator specification" is "even more vulnerable to data mining than is identification of the basic regularities".

### Are tweaked factor related to standard factors?

In the absence of a clear relation with academic standard factors, proprietary factor strategies are merely ad-hoc constructs resulting from product back-tests. In fact, to find out whether any of these new proprietary factors are indeed related to the well-documented academic factors one would first need to assess how they align empirically with standard factors. This point was also made clear by Eugene Fama in a recent interview, when on the topic of Value factor and more proprietary versions of this factor he stated "*Now everybody talks about Value.... Some stuff is fly-by-night. There are like 45 versions of that and every guy has their own marketing ploy. The acid test is you put it in the three factor model and it says it is a value portfolio.*"<sup>137</sup>

To ensure that the insights from academic finance on factor investing benefit factor investing strategies in practice, one should avoid taking too much liberty with the factor definitions used in the academic publications that established the field and which are supported by independent empirical evidence and economic justifications. Moreover, as underlined by Merton (1980)<sup>138</sup>, it is notoriously difficult to estimate expected returns, and therefore

135 - Pedersen, L. H. 2015. Efficiently Inefficient: How Smart Money Invests & Market Prices Are Determined. Princeton University Press.

136 - Ilmanen, A., 2011. Expected Returns: An Investor's Guide to Harvesting Market Rewards. Chichester: John Wiley & Sons.

137 - Q&A with Eugene Fama, Fiduciary Investors Symposium, top1000funds.com/Conexus Financial, October 18-20, 2015 - recording available at: <http://www.top1000funds.com/featured-homepage-posts/2015/12/11/investors-from-the-moon-fama/>

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

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one may be well advised to avoid trying to increase returns of factors through various tweaks and instead focus on applying risk-based diversification strategies to factor-based selections since risk parameters can be estimated using robust techniques.

### Conclusions and requirements for good practice

In the end, a sensible requirement for good practice in factor investing seems to be to avoid creating a mismatch with academic factors. This can be achieved easily by referring to indicators for which academic research has provided thorough tests and economic explanations, and by refraining from proprietary "tweaks".

Given the strong emphasis providers put on the "academic grounding" of their factor strategies, it is indeed surprising that they then choose to implement products that take extreme liberty with academic factor definitions and do not respect the key academic principle of parsimony. Instead of paying lip service to an "academic grounding" and coming up with marketing innovation of tweaked factors, perhaps it is time that product providers actually used academic research in their product development. Investors could help by holding providers to high standards and conducting thorough due diligence on the soundness of particular implementations of factor investing.

Investors would be wise to interpret provider claims that factor investing requires a sophisticated, customised, scoring approach, as invitations to factor fishing parties. While such parties do not qualify as inducements, fiduciaries be wary of awarding factor fishing licenses and increasing the degrees of freedom that providers can use to improve back-tested

performance with adverse consequences for robustness.

As we have shown in our empirical illustrations, the out-of-sample degradation of most of the strategies selected on the basis of favourable in-sample performance is a real risk to investors. Strategies that rely on promising in-sample performance rarely deliver on their promises out-of-sample. Our simulations also showed that searching for new factor definitions hardly brings any added value compared to using simple and time-tested metrics, such as Book-to-Market in the case of Value.

With the advance of modern data processing tools and the ever-increasing amount of data, the temptation to mine for attractive in-sample results is higher than ever before. Investors should carefully evaluate the relevance of the back-test and assess the reliability and robustness of the results of any portfolios to avoid the trap of data-mining.

It is also worth emphasising that a key idea behind the use of standard factors is to obtain robustness through parsimony. Parsimony refers to the idea that one can explain "a lot" with "a little. While proprietary factor definitions may be able to explain more in sample, they also pose a risk of picking up sample noise, which one can avoid with more parsimonious factor definitions such as the ones used in the reference literature. The statistician George E. P. Box famously argued in favour of parsimony by writing that "*over-elaboration and over-parameterization is often the mark of mediocrity.*" Indeed, the parsimony of standard academic equity factor definitions may be preferable to over-elaboration and over-parameterisation of tweaked proprietary factors that are sometimes proposed by product providers.

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## 10) The Factor Purity Argument: "A good factor index needs to isolate exposure to the target factor"

### Overview of the claim

Some argue that a factor index should not only provide the exposure to an intended factor but also neutralise any exposure to other factors. For example, Hunstad and Dekhayser (2015)<sup>139</sup> criticise Smart Beta indices that may be "unable to provide desired factor exposures without taking on substantial unintended exposures" and lament that such indices "are not 'pure' in their delivery of intended factor exposures".

It is useful to point out several questions regarding the relevance of assessments of purity of factor indices.

### What are the definitional difficulties with purity?

The objective of designing pure indices is problematic because the measured "purity" of an index does not only depend on a decision regarding the target factor or factors but may also be highly dependent on the factor model chosen to measure factor exposures. This implies that purity is a highly subjective attribute: A Smart Beta strategy may show high purity according to a given and subjective purity measure but be judged of a lower grade by other equally subjective purity measures.

In fact, using different types of commercial models such as the Barra or Axioma or Sunguard models or different types of academic models such as the Fama-French (1993) and Carhart (1997) models would lead to different results, because the set of factors included in each model changes and factors that appear to be common to different models may in fact have very different definitions. A given factor in a given model, say the Barra Value factor, which is the benchmark for purity within this particular model, will not be purely exposed to

Value when analysed in the Fama-French or Carhart models. By extension, the purity of any factor index or portfolio will always be relative to a particular model, rather than an absolute characteristic of that index or portfolio.

### What are the implementation issues with pure factors?

If we assumed for a moment that there existed a golden standard by which to measure purity, one would then be faced with the fact that factor purity is not of the long-only world of asset management. In fact, for the light of purity to shine, shorting would be necessary to capture a single factor while hedging out all exposures to other factors precisely. The implementation challenges with long/short approaches have been well documented. Huij et al. (2014)<sup>140</sup> study the difference between the long/short and long-only factor proxies and conclude that: "although a long-short approach is superior theoretically, a long-only approach seems to be the preferred alternative in most scenarios, after accounting for practical issue". It thus appears reasonable to use long-only factor indices although they cannot be pure.

While there are indeed some indices that have built in a purity objective in their methodology, they have been the victims of implementation challenges this poses, and have failed to acquire a wide following as a result. For example, both MSCI and Russell publish factor indices which target exposure to a particular factor while explicitly controlling the exposure to other factors (the MSCI Barra Factor Indices, and the Russell-Axioma Factor Indices). The Russell-Axioma Factor Indices gave rise to ETFs that were launched in 2011 (Axioma (2011)<sup>141</sup>) and then closed down in 2012

139 - Hunstad, M., and J. Dekhayser, 2015. Evaluating the Efficiency of 'Smart Beta' Indexes, *Journal of Index Investing* (Summer issue).

140 - Huij, J. S. D. Lansdorp, D. C. Blitz and P. van Vliet. 2014. Factor Investing: Long-Only versus Long-Short. SSRN working paper.

141 - Axioma. "Russell Launches Series of Ten 'Factor' ETFs based on Russell - Axioma Indexes". Thursday, June 2nd, 2011. Available at: <http://www.axioma.com/news/articles/russell-launches-series-of-ten-factor-etfs-based-on-russell-axioma-indexes/>

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(Levisohn (2012)<sup>142</sup>). Bender et al. (2013)<sup>143</sup> note that pure indices suffer from low investability as investability decreases from long-only indices to long/short indices, and then becomes even lower for pure indices. Given their severe implementation problems, it is no surprise that such indices are not widely used in practice.

### Do the academic foundations on factor investing make the case for pure indices?

Given that factor indices are largely motivated by the academic groundings of the associated risk premia, it is useful to look at what the key papers on factor investing have to say on purity requirements.

It is clear from the construction and analysis of empirical asset pricing factors in the literature that such factors are not pure. Factor returns are somewhat correlated and this is not seen as an issue. In fact, Fama and French (2015)<sup>144</sup> discuss in detail why purity is not a reasonable objective. "Since [value],[profitability], and [investment] are correlated, the 25 Size-Value, Size-Profitability, and Size-Investment portfolios do not isolate value, profitability, and investment effects in average returns. To disentangle the dimensions of average returns, we would like to sort jointly on Size, Value, Profitability, and Investment, but we would quickly sacrifice portfolio diversification." Due to this problem with multiple sorting that attempts to isolate a "pure" factor, they settle on using much simpler two-by-two sorts based on only a size control and then sorting on the relevant variable. This allows reasonably diversified portfolios to

be maintained whereas the sorts that attempt to control for more factors end up producing highly concentrated portfolios. It is apparent that achieving purity is not seen as a main concern. But having well-diversified portfolios is.

Moreover, it is obvious from papers introducing additional factors to Value and Small Cap that such factors are not entirely unrelated to Value and Size. For example, papers that have discussed the Momentum factor, the Low Volatility factor, and the Profitability factor, typically show the power of such factors in explaining returns over and above what is already explained by factors such as Value and Size (see e.g. Jegadeesh and Titman (1993)<sup>145</sup>, Blitz et al. (2007)<sup>146</sup>, Novy Marx (2013)<sup>147</sup>). In the process of doing this, such research commonly adjusts the returns to such new factors by their exposure to Value and Size. It has been documented in particular that Low Volatility factor returns are positively correlated to the Profitability factor (see Fama and French (2016)<sup>148</sup>), and the Momentum and Profitability factor are negatively correlated to the Value factor (see Asness et al. (2013)<sup>149</sup> and Hou et al. (2015)<sup>150</sup>). The fact a given factor is not free of exposure to other factors is well known. Why this would be a problem is not clear.

### Targeting precise factor risk contributions without pure factor indices

It should also be pointed out that the existence of uncorrelated long-short factor replicating portfolios is not a necessary condition to perform risk budgeting, which

142 - Levisohn, B. "Russell ETFs, We Hardly Knew Ye". *Wall Street Journal* Aug 20, 2012. Available at: <http://blogs.wsj.com/totalreturn/2012/08/20/russell-etfs-we-hardly-knew-ye/>

143 - Bender, J., R. Briand, D. Melas, R. A. Subramanian, and M. Subramanian. "Deploying Multi-Factor Index Allocations in Institutional Portfolios". MSCI Research Insight, December 2013. Available at: [https://www.msci.com/resources/pdfs/Deploying\\_Multi\\_Factor\\_Index\\_Allocations\\_in\\_Institutional\\_Portfolios.pdf](https://www.msci.com/resources/pdfs/Deploying_Multi_Factor_Index_Allocations_in_Institutional_Portfolios.pdf)

144 - Fama, E. F. and K. R. French. 2015a. A Five-Factor Asset Pricing Model. *Journal of Financial Economics* 116(1): 1-22.

145 - Jegadeesh, N. and S. Titman. 1993. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance* 48(1): 65-91.

146 - Blitz, D. and P. Van Vliet. 2007. The Volatility Effect: Lower Risk without Lower Return. *Journal of Portfolio Management* 34(1): 102-113.

147 - Novy-Marx, R. 2013. The Other Side of Value: The Gross Profitability Premium. *Journal of Financial Economics* 108(1): 1-28.

148 - Fama, E. F. and K. R. French. 2016. Dissecting Anomalies with a Five-Factor Model. *Review of Financial Studies* 29(1): 69-103.

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

150 - Hou, K., C. Xue and L. Zhang. 2015. Digesting Anomalies: An Investment Approach. *Review of Financial Studies* 28(3): 650-705.

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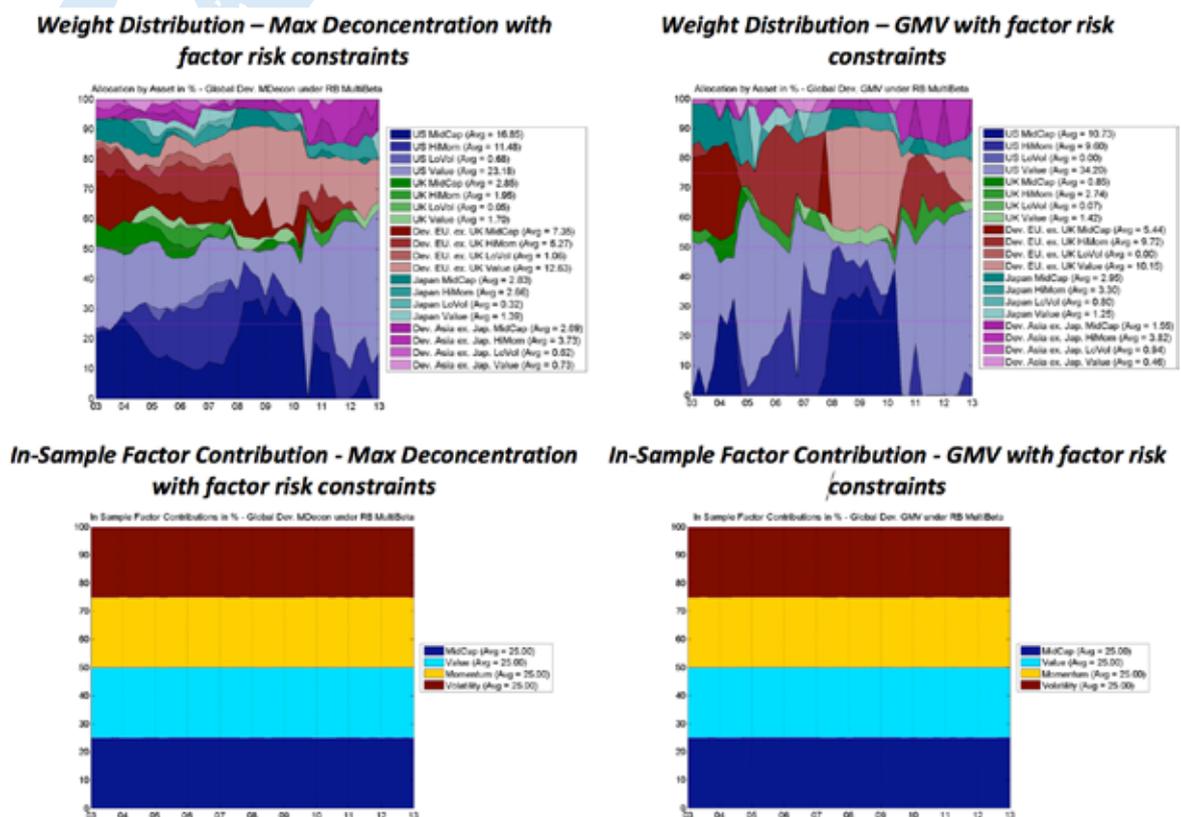
is fortunate since such uncorrelated pure factors are hardly investable in practice. Indeed, one can use any set of well-diversified portfolios, as opposed to factor-replicating portfolios, as constituents, leaving to the asset allocation stage the hurdle to reach target factor exposures.

For example, Amenc et al. (2014)<sup>151</sup> use long-only factor-tilted Smart Beta benchmarks as constituents and choose the allocation to these constituents so as to ensure that the contribution of standard rewarded equity factors to the volatility of the portfolio are all equal. This is known as factor risk parity. Amenc et al. (2014) show that the absence of total purity of the factor replicating portfolios (i.e. the fact that long-only factor indices have betas not equal to zero with respect to other factors) or of the factors themselves

(i.e. the fact that the factors are correlated even in their long-short version), is not a strong problem per se as long as such biases can be measured and controlled for using suitably-designed factor risk budgeting constraints.

In particular, Amenc et al. (2014) study portfolios allocating to Smart Factor Indices (which are not designed to be pure) and look at two allocation methodologies – Maximum Deconcentration and Global Minimum Variance (GMV) while imposing as a constraint that the resulting contributions from risk factors be identical (factor risk parity). Both allocation methods are imposing factor risk parity while also respecting geographical constraints so as to avoid excessive regional deviations.<sup>152</sup> The exhibit below shows the results reported in Amenc et al. (2014) who show that factor

*Exhibit 23: Max Deconcentration and GMV Allocations under Risk Factor and Geographical Constraints (Developed Universe). The graph shows the allocations and factor contributions of the max-deconcentration and GMV Diversified Multi-Strategy indices invested in the twenty Diversified Multi-Strategy indices with stock selection based on mid cap, momentum, low volatility, and value in the five US, UK, Dev. Europe ex UK, Japan and Asia Pacific ex Japan sub-regions. Both risk parity and geographical constraints are imposed onto the resulting portfolios. The period is from 31-December-2003 to 31-December-2013. Taken from Amenc et al. (2014).*



151 - Amenc, N., R. Deguest, F. Goltz, A. Lodh, L. Martellini, and E. Shirbini. "Risk Allocation, Factor Investing and Smart Beta: Reconciling Innovations in Equity Portfolio Construction". EDHEC-Risk Institute, 2014 (July). Available at: [http://docs.edhec-risk.com/mrk/000000/Press/EDHEC-Risk\\_Publication\\_Risk\\_Allocation.pdf](http://docs.edhec-risk.com/mrk/000000/Press/EDHEC-Risk_Publication_Risk_Allocation.pdf).  
152 - For details of the optimisation algorithm, consult the original paper

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risk parity can be achieved as a constraint when using these allocation methods to allocate across Smart Factor Indices which are not pure in terms of their factor exposures.

The exhibit shows that both the Maximum Deconcentration approach and the Global Minimum Variance approaches for allocating across Smart Factor Indices can be implemented while respecting the constraint of equal risk contributions from each of the factors. This requires a dynamic risk-based allocation across the constituent Smart Factor Indices. It thus appears as a conclusion that when precise targeting of risk-factor exposures matters, purity of factor indices is not a requirement as long as suitably designed risk budgeting techniques are employed to allocate across factor indices. Both resulting portfolios satisfy the factor risk parity which is achieved by the dynamics of the weight changes between the constituting Smart Beta portfolios. The allocation fulfils its second objective too, i.e. the geographical blocks are distributed in line with market capitalisation.

### Who cares about purity?

Purity is difficult to achieve at the individual factor index level. When trying to create pure factors one ends up with formidable implementation challenges. However, this is not necessarily a problem. For example, the standard Fama and French or Carhart factors are neither designed to be pure nor to be uncorrelated in the data. This in no way questions the academic relevance of these factors as being useful in explaining the cross section of expected stock returns nor their practical relevance as useful sources of additional returns relative to those delivered by a broad equity market exposure. Likewise, the fact that commonly

used factor indices are not pure does not question their usefulness for investment portfolios, given that factor purity is not likely to be an objective in most investment contexts. Moreover, if one wants to control exposure to multiple factors one does not need pure factor indices as building blocks as one can rely on state-of-the-art risk allocation processes to build and manage a portfolio of impure but easy-to-implement and well-diversified factor indices that will jointly deliver the desired risk contributions.

In the end, a focus on purity is rarely warranted and will necessarily come at the expense of diversification and ease of implementation, which are first-order issues with factor indices.

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# General Conclusions

## General Conclusions

That a new investment approach be debated should not be surprising. Such debate should be expected to further the understanding of potential benefits as well as risks and possible pitfalls of the new approach. In the area of Smart Beta investing however, an intense debate has also produced a certain number of beliefs which are accepted as conventional wisdom and impede progress towards the adoption of approaches that could add more value for end investors.

The objective of this paper was to provide perspective on these beliefs by examining conceptual considerations and empirical evidence. The analysis of the ten items in this paper shows that, more often than not, superficially convincing claims about Smart Beta strategies stand on shaky foundations. Our analysis also shows that challenging conventional wisdom by reviewing the extant academic literature and empirical evidence may perhaps lead to more balanced conclusions and a more nuanced understanding of the benefits and risks of Smart Beta strategies.

To be sure, research on the benefits and risks of Smart Beta strategies is still ongoing and this, along with more data on the live performance of strategies becoming available, could help refine our understanding of the issues at hand.

It is important to underline that our analysis does not aim to provide definite conclusions on all Smart Beta strategies. In fact, all too often, claims about the benefits or risks of Smart Beta abstract from the variety of approaches that exist. The analyses in this paper show that accounting for the differences across strategies is necessary to avoid rushing to premature conclusions. Indeed, many of the misconceptions debunked in this paper

correspond to over-generalisations which, willingly or not, fail to acknowledge that the term Smart Beta covers a vast variety of strategies with potentially very different properties. In a nutshell, our analysis cautions against such over-simplification and calls for a rigorous and detailed analysis of Smart Beta strategies.

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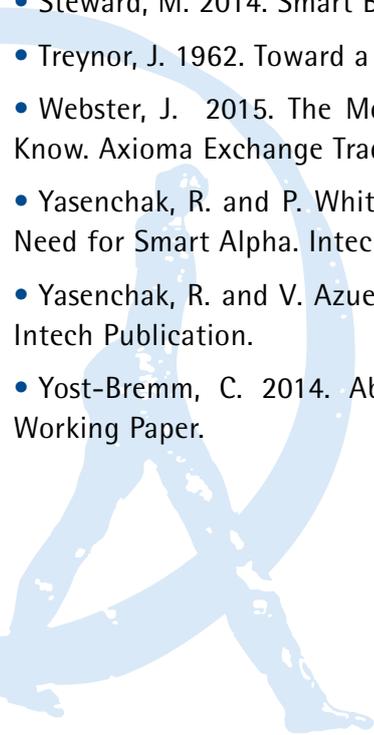
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**EDHEC-Risk Institute  
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- Maeso, J.M., L. Martellini. Factor Investing and Risk Allocation: From Traditional to Alternative Risk Premia Harvesting (May).
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