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The Dimensions of Quality Investing: High Profitability and Low Investment Smart Factor Indices

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Table of Contents

Introduction 5

1. High Profitability and Low Investment as Factors 9

2. Smart Factor Indices for High Profitability and Low Investment Tilts 19

3. Combining High Profitability and Low Investment Factors 31

4. Comparison of Industry Offerings 37

Conclusion 43

References 45

About ERI Scientific Beta 49

ERI Scientific Beta Publications 53

Abstract

Asset pricing theory postulates that multiple sources of systematic risk are priced in securities markets. Of late, we have seen a sudden proliferation of factor investing strategies that seek exposures to various factors from asset managers and index providers all over the world. At the same time, a new approach to equity investing, referred to as smart factor investing, provides an assessment of the benefits of addressing simultaneously the two main shortcomings of cap-weighted indices: their undesirable factor exposures and their heavy concentration. It constructs factor indices that explicitly seek exposures to rewarded risk factors while diversifying away unrewarded risks. The results we obtain suggest that such smart factor indices lead to considerable improvements in risk-adjusted performance. In line with the academic approach that guides Scientific Beta's work and index offerings, the number of smart factors offered is limited to those that are the subject of academic consensus with regard to both their long-term reward and their construction method. As such, Scientific Beta has based its multi-factor approaches on four smart factor indices: Value, Momentum, Size and Low Volatility.

More recently, two new rewarded risk factors have been identified in the literature as not only providing high risk premia in the long run based on empirical evidence but also having simple and straightforward economic explanations for the existence of their premia, providing reassurance on the robustness and persistence of the factors. High Profitability and Low Investment are the two factors. Several commercial index providers are marketing indices under the label "Quality Factor Indices" which supposedly seek the premium associated with these two factors.

In this paper, we discuss the literature and evidence found so far in support of the two factors. We also discuss various arguments and explanations surrounding the reasons for expecting a premium out of the two factors. We also discuss Scientific Beta's smart factor approach to gaining exposure to High Profitability and Low Investment factors that provide a well-diversified way to seek the factor risk premia. We briefly discuss Scientific Beta's implementation methodology, the choice of proxy variables and the performance of the two factor indices. We also explore the possibility of combining the two smart factor indices to form a multi-factor index that gains exposure to both factors simultaneously. Finally, we review some of the "quality" indices marketed by competitors and their methodology, and we perform a comparative study with Scientific Beta's smart factor indices.

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Introduction

Introduction

Asset pricing theory postulates that multiple sources of systematic risk are priced in securities markets. In particular, both equilibrium models such as Merton's (1973) intertemporal capital asset pricing model and no arbitrage models such as Ross's (1976) Arbitrage Pricing Theory allow for the existence of multiple priced risk factors. The economic intuition for the existence of a reward for a given risk factor is that exposure to such a factor is undesirable for the average investor because it leads to losses in bad times[1] (i.e. when marginal utility is high, see e.g. Cochrane 2000). Therefore, it may be perfectly reasonable for an investor to shun exposure to such risk premia despite their long-term reward. Large institutional investors, however, who are often investing over a long-term horizon, may be well positioned to take on such risks. It should be noted that such exposures thus correspond to additional betas, i.e. exposure to rewarded risk factors, which exist because the average investor is averse to taking on such risk. Alternative explanations for the reward to these factors consider such factors as alpha, because they generate returns that are not just compensation for risk. In particular, the existence of rewards for factors such as value and momentum has been related to behavioural biases of investors. The claim is that since investors make systematic errors, such as under-reacting or over-reacting to information, mispricing exists in the market and can be exploited. However, such behavioural phenomena can only influence asset prices if, in addition to the existence of the errors of irrational investors leading to anomalies, there are no rational investors who are able to arbitrage such anomalies away. Such limits to arbitrage exist in the form of short sales constraints and investors' funding liquidity constraints. However, it is important to stress that assuming irrational behaviour and "mispricing" is not necessary for the existence of such factor premia. In the framework of multi-factor asset pricing, they can be explained rationally, by the requirement of investors to be rewarded for taking on exposure to risk factors that lead to losses in bad times. It is in this sense that exposure to such factors can be appropriately described as "beta."

Of late, we have seen a sudden proliferation of factor investing strategies that seek exposures to various rewarded risk factors from asset managers and index providers all over the world. Naturally, some factors may provide stellar performance over a given short-term back-test period but may not be valid over the long term if such factors are not systematic risk factors that carry a long-term reward. Therefore, our approach has been to be parsimonious in considering what a rewarded risk factor is, and thus a candidate for Scientific Beta's multi-beta indices. These indices only include the four main factors; value, momentum, size and low volatility. Other factors are of course provided on the Scientific Beta platform such as "high dividend" or "low liquidity," and may be suitable building blocks employed in tactical allocation choices among factors, even those that are not rewarded in the long term.

However, having access to a proxy for a factor is hardly relevant if the investable proxy only gives access to a fraction of the fair reward per unit of risk to be expected from the factor exposure because of the presence of unrewarded risks (due to excessive concentration, for instance). A relevant question is thus how to best extract the premium for a factor in an efficient way. Amenc et al. (2014a) address this question in detail. The authors present how the Smart Beta 2.0 approach

1 - It is worth emphasising that asset pricing theory suggests that factors are (positively) rewarded if and only if they perform poorly during bad times, and more than compensate during good times so as to generate a positive excess return on average across all possible market conditions. In technical jargon, the expected excess return on a factor is proportional to the negative of the factor covariance with the pricing kernel, given by marginal utility of consumption for a representative agent. Hence, if a factor generates an uncertain payoff that is uncorrelated to the pricing kernel, then the factor will earn no reward even though there is uncertainty involved in holding the payoff. On the other hand, if a factor payoff covaries positively with the pricing kernel, it means that it tends to be high when marginal utility is high, that is when economic agents are relatively poor. Because it serves as a hedge by providing income during bad times, when marginal utility of consumption is high, investors are actually willing to pay a premium for holding this payoff.

Introduction

(Amenc et al., 2013), the main idea of which is to apply a smart weighting scheme to an explicit selection of stocks, enables the construction of factor indices which are not only exposed to the desired risk factors, but also avoid being exposed to unrewarded risks. This approach, referred to as "smart factor indices" can be summarised as follows. The explicit selection of stocks provides the desired tilt, i.e. the beta, while the smart weighting scheme addresses concentration issues and diversifies away specific and unrewarded risks. Thus, the Smart Beta 2.0 approach constructs factor indices that explicitly seek exposures to rewarded risk factors, while diversifying away unrewarded risks. We call these indices "smart factor" indices. The results we obtain suggest that such smart factor indices lead to considerable improvements in risk-adjusted performance.

The flexible index construction process used in second generation smart beta indices thus allows the full benefits of smart beta to be harnessed, where the stock selection defines exposure to the right (rewarded) risk factors and the smart weighting scheme allows unrewarded risks to be reduced.

In particular, we consider the following criteria to define the rewarded factors:

Volatility	Valuation	Momentum	Size	Investment	Profitability
Low Vol	Value	Winner	Mid Cap	Low Invst.	High Prof.
High Vol	Growth	Loser	Large Cap	High Invst.	Low Prof.
Volatility of weekly returns over past 2 years	Book to Market ratio	Past one year (minus 1-last month) returns	Free float adjusted market cap	Total Asset Growth over past 2-years	Gross profit to Total Asset ratio

More recently, two new rewarded risk factors have been identified in the literature which not only provide high risk premia in the long run based on empirical evidence but also have simple and straightforward economic explanations for the existence of their premia, guaranteeing the

Introduction

robustness and persistence of the factors. High Profitability and Low Investment are the two factors. Several commercial index providers are marketing indices under the label "Quality Factor Indices" which supposedly seek the premium associated with these two factors.

In this paper, we discuss Scientific Beta's smart factor approach to gaining exposure to High Profitability and Low Investment factors that provide a well diversified way to seek the factor risk premia and perform a comparative study of Scientific Beta's High Profitability and Low Investment smart factor indices with those of its competitors.

1. High Profitability and Low Investment as Factors

1. High Profitability and Low Investment as Factors

1.1. Evidence-Based "Quality" Definitions

Asset managers and index providers are increasingly touting the benefits of quality investing. Such strategies tilt portfolios to "high quality" stocks, as characterised for example by high profitability, stable earnings, or low leverage, to name but a few of the variables used in practice. However, asset managers and index providers do not use a common definition of "quality," and a wide variety of approaches exist. Two different factors have been introduced in the empirical asset pricing literature to proxy two different dimensions of so-called "Quality":

Profitability
e.g. Gross Profitability

$$Gross\ Profitability_t = \frac{Revenue_{t-1} - COGS_{t-1}}{Total\ Assets_{t-1}} \quad (1)$$

Investment
e.g. Growth of Total Assets

$$Total\ Asset\ Growth_t = \frac{Total\ Assets_{t-1} - Total\ Assets_{t-3}}{Total\ Assets_{t-1}} \quad (2)$$

High Profitability and Low Investment have recently been identified as rewarded risk factors in the long run. There has been strong evidence and a straightforward economic explanation for the existence of a premium for these two factors and extensive literature has come up with many multi-factor asset pricing models that include these factors in their models. The academic literature describes profitability and investment as two different risk factors, each with its own risk premium. However, commercial index providers often bundle these factors and brand them as "Quality" indices.

1.1.1. Picking Quality Stocks vs Quality Factor Investing

The premise of quality investing is that high quality stocks are not sufficiently recognised by the market to increase their price to a level that fully reflects their superior quality - therefore such stocks offer a good investment opportunity. These approaches try to add alpha in a systematic way akin to what a stock picker does. The concept has been traced back to fundamental stock pickers such as Benjamin Graham, Jeremy Grantham and Joel Greenblatt. The stock picking philosophy appears to be based on a naive belief that systematic rebalancing of an index based on accounting data allows alpha to be generated. In practice, systematic screening offered today by numerous index providers aims to procure alpha in competition with traditional asset managers, without necessarily having all of the same characteristics, and notably the capacity to take account of forecasts on the evolution of stock characteristics or new factors that can change the perception of those characteristics.

For academics and proponents of a beta, rather than an alpha, approach, which in our view is the only approach that is compatible with index investment, the term "quality" refers to a completely different dimension: the factor approach.

1. High Profitability and Low Investment as Factors

Rational factor investing does not rely on finding underpriced stocks, but rather seeks to identify factors that lead to systematic risks which investors are unwilling to bear without a commensurate reward. The factor-based approach is founded on asset pricing theory and tries to design factor indices or smart factor indices based on the idea that there are long-term rewarded risks, i.e. the focus is on betas (exposures with respect to common risk factors). It therefore does not require an ability to pick stocks by processing information in a superior fashion compared to the market. Rather, it tries to identify risk factors with a strong economic rationale, and considerable empirical evidence in favour of a positive risk premium. Interestingly, recent research has identified a set of fundamental characteristics, which are similar to some of the descriptors of "quality," namely high profitability and low investment. For example, Asness (2014) notes that quality measures tend to "overlap with the profitability and investment factors." Both these factors have been found to be relevant in explaining the cross section of stock returns. Such factors would be straightforward alternatives to ad-hoc definitions of quality used in the asset management industry currently. The advantage of these factors is that they have been widely documented, extensively tested in the data by many academics independently, and thoroughly explained in terms of economic mechanisms underlying the associated premia.

1.1.2. Straightforward and Proven Factors

More recently, authors have documented profitability and investment as factors which explain the cross-section of stocks returns (see e.g. Fama and French, 2014; Novy-Marx, 2013, Cooper et al., 2008, Titman et al., 2004). Although the authors differ on characteristics that can be used as a proxy for profitability or investment factor, they present robust evidence that there is a premium associated with these factors. They also emphasise that profitability or investment factors are not manifestations of other well-documented factors such as the value factor. For example, Novy-Marx (2013) notes that profitability exhibits negative correlation with the value factor. Similarly, Cooper (2008) notes that the investment factor is a significant explanatory factor, even after controlling for factors such as value, size and momentum. The authors have found that the stocks of firms with high profitability tend to have higher returns and those firms with low investment in the current period typically measured by asset growth tend to have higher returns in the next period. These factors are straightforward, consistent with asset pricing theory, and have well-documented empirical evidence in addition to theoretical justification in the academic literature. The reasoning on why a risk premium is expected from these two factors is elaborated upon in the next section.

Exhibit 1: Factor Discovery and Reference Literature

	Factor Definition	Within US Equities	International Equities
High Profitability	Stocks of firms with high profitability (gross profitability or return on equity) have high returns	Novy-Marx (2013), Hou, Xue and Zhang (2014a, 2014b), Fama and French (2014)	Ammann, Odoni, Oesch (2012)
Low Investment	Stocks of firms with low investment (e.g. change in total assets or change in book-value) have high returns	Cooper, Gulen, and Schill (2008), Aharoni et al. (2013), Hou, Zhang and Xue (2014a, 2014b), Fama and French (2014)	Ammann, Odoni, Oesch (2012), Watanabe, Xu, Yao, Yu (2013)

1. High Profitability and Low Investment as Factors

1.2 Justification of "Quality" Factors

1.2.1 Economic Mechanisms at Work

Several authors have provided an economic rationale for these factors. It is interesting to note that the economic justification of such factors is arguably much more straightforward than the motivation for others factors such as size, value and momentum. In fact, Hou, Xue and Zhang (2014b) argue that, since the investment and profitability factors should influence expected returns according to production-based asset pricing theory, using these factors "is less subject to the data-mining critique than the Fama-French model." Two explanations suggesting a role for these factors are summarised below:

Dividend Discount Model

Fama and French (2006) derive the relationship between book-to-market ratio, expected investment, expected profitability and expected stock returns from the dividend discount model, which models the market value of a stock as the present value of expected dividends:

$$M_t = \sum_{\tau=1}^{\infty} E(D_{t+\tau})/(1+r)^{\tau} \quad (3)$$

Using the fact that, with clean surplus accounting, dividends equal equity earnings per share minus the change in book equity per share we have:

$$M_t = \sum_{\tau=1}^{\infty} E(Y_{t+\tau} - dB_{t+\tau})/(1+r)^{\tau} \quad (4)$$

and dividing by book equity yields:

$$\frac{M_t}{B_t} = \sum_{\tau=1}^{\infty} \frac{E(Y_{t+\tau} - dB_{t+\tau})/(1+r)^{\tau}}{B_t} \quad (5)$$

These equations lead to the following three predictions:

- Controlling for expected earnings and expected changes in book equity, high book-to-market implies high expected returns
- Controlling for book-to-market and expected growth in book equity, more profitable firms (firms with high earnings relative to book equity) have higher expected return
- Controlling for book-to-market and profitability, firms with higher expected growth in book equity (high reinvestment of earnings) have low expected returns.

The second and third predictions of the dividend discount model mentioned above justify the profitability and investment premia, i.e. high return on profitable firms compared to less profitable firms and high return on low investment firms compared to high investment firms.

1. High Profitability and Low Investment as Factors

Production-based Asset Pricing

Hou, Xue and Zhang (2014b) provide a more detailed economic model where profitability and investment effects arise in the cross section due to firms' rational investment policies (also see Liu, Whited and Zhang, 2009). In particular, a firm's investment decision satisfies the first order condition that the marginal benefit of investment discounted to the current date should equal the marginal cost of investment. Put differently, the investment return (defined as the ratio of the marginal benefit of investment to the marginal cost of investment) should equal the discount rate. This optimality condition means that the relationship between investment and expected returns is negative: if expected investment is low, expected returns are high. Intuitively (given expected cash flows), firms with a high cost of capital (and thus high expected returns) will have difficulty finding many projects with positive NPV and thus not invest a lot. The optimality condition further implies a positive relationship between profitability and expected returns. High profitability (i.e. high expected cash flow relative to equity) at a given level of investment implies a high discount rate. Intuitively, if the discount rate was not high enough to offset the high profitability, the firm would face many investment opportunities with positive NPV and thus invest more by accepting less profitable investments.

	Rational Explanation	Behavioural Explanation
High Profitability	Firms facing high cost of capital will focus on the most profitable projects for investments	Investors do not distinguish sufficiently between growth with high expected profitability and growth with low profitability, leading to under-pricing of profitable growth firms
Low Investment	Low investment reflects firms limited scope for projects given high cost of capital	Investors under-price low investment firms due to expectation errors

1.3. Empirical Literature Survey

1.3.1. Factor Definitions in the Literature

We have discussed the possible explanations and economic rationale for why a premium is possible for the profitability and investment factors. In this section and the next section we discuss how the factor premia associated with the two factors can be harvested and if there is any empirical evidence supporting the existence of the premia. As with any risk factor, we need an observable and measurable proxy variable for each risk factor. Gross Profitability and Asset Growth are the two proxy variables most widely analysed and tested in the academic literature. The tables below summarise the proxy variables and their definitions as defined by various authors in their implementation of multi-factor asset pricing models.

Exhibit 2: Profitability Proxy Variable

Paper	Profitability Proxy	Key findings
Novy-Marx (2013)	Revenue minus Cost of Goods Sold divided by Total Assets	Gross Profitability factor generates positive risk-adjusted returns relative to factors in the Fama and French/Carhart multi-factor model
Hou, Xue, and Zhang (2014)	Income before Extraordinary Items/Book Equity	A four-factor model (market, value, size, and profitability/investment) explains most cross-sectional return patterns and profits from many well known profitable trading strategies.
Fama and French (2014)	Operating Profit/Book Equity	Five-factor model (market, value, size, profitability and investment) explains 69%-93% of cross-sectional variation in expected returns.

1. High Profitability and Low Investment as Factors

Exhibit 3: Investment Proxy Variable

Paper	Investment Proxy	Key findings
Hou, Xue, and Zhang (2014)	Change in Total Assets	A four-factor model (market, value, size, and profitability/investment) explains most cross-sectional return patterns and profits from many well known profitable trading strategies.
Fama and French (2014)	Change in Total Assets (Change in Book Equity)	Five-factor model (market, value, size, profitability and investment) explains 69%-93% of cross-sectional variation in expected returns.

While various definitions of profitability exist in the literature, we use the Gross Profitability definition from Novy-Marx (2013). Given the lack of serious information on the accounting treatment of R&Dand other discretion involved in reporting net profit, we prefer this measure over the ROE measure. This approach remains consistent with Fama and French's (2014) definition of profitability, which when applied to empirical data could lead in certain geographic regions where accounting rules allow for numerous options, to results that may not be consistent with the literature.

Our choice of method in terms of the proxy we employ for these factors that have been documented in the financial literature certainly take the accounting difficulties into account in practice. We have preferred to remain parsimonious to avoid the risk of relying on accounting treatments.

We also note that using assets in the denominator is consistent with an approach where one aims to avoid favouring heavily-indebted firms, as gross profits do not include interest expenses. In the end, gross profitability is not chosen just for its usefulness per se, but also for its usefulness as a robust and parsimonious proxy for expected profitability, in the sense of the required profitability of the firm's investment project to account for its cost of capital.

1.3.2. Empirical Evidence

There is in fact ample empirical evidence suggesting that investment and profitability are important determinants of the cross section of stock returns.

On the one hand, profitability is typically proxied as return on equity (ROE), defined as net income divided by shareholders' equity (book value of equity). The corresponding factor is based on sorting stocks by ROE into portfolios and creating a zero-investment strategy called Profitable Minus Unprofitable (PMU). The outperformance of profitable over unprofitable companies has been documented in a recent paper by Novy-Marx (2013), who shows that profitable firms generate higher returns than unprofitable firms. Novy-Marx insists on the importance of using gross profits rather than accounting earnings to determine profitability. Cohen, Gompers and Vueltenhao (2002) provide similar evidence showing that—when controlling for book-to-market—average returns tend to increase with profitability. On the other hand, investment is typically defined as asset growth (change in book value of assets over previous year). The corresponding factor is based on sorting stocks by asset growth into portfolios and creating a zero investment strategy called Conservative Minus Aggressive (CMA). Cooper, Gulen and Schill (2008) show that a firm's asset growth is an important determinant of stock returns. In their analysis, low-investment firms (firms with low

1. High Profitability and Low Investment as Factors

asset-growth rates) generate about 8% annual outperformance over high-investment firms (firms with high asset growth rates). Titman, Wei, and Xie (2004) show a negative relationship between investment (which they measure by the growth of capital expenditures) and stock returns in the cross section. A negative relationship between investment and stock returns is also documented by Xing (2008) and Lyandres, Sun, and Zhang (2008) who use yet other firm characteristics to proxy for investments. Ahroni, Grundy and Zeng (2013) show that even when controlling for profitability and book-to-market there is a negative relationship between investment and returns.

The empirically-observed effects of investment and profitability have led other researchers to integrate these factors in multi-factor models, with some models accounting for both effects simultaneously. More often than not, authors augment standard models, such as the Fama and French three-factor model with these new factors, but some authors propose to replace the standard factors with the new factors. It is interesting to summarise the evidence produced in this context on the dependence between the different factors.

Novy-Marx (2013) considers a four-factor model including the market factor, and (industry-adjusted) value, profitability and momentum factors. He argues that this four factor model does a good job of explaining returns of a broad set of profitable trading strategies (including strategies seeking to exploit earnings surprises, differences in distress scores, earnings-to-price effect, etc.)
Hou, Xue and Zhang (2014b) use a four-factor model including a market factor, a size factor, an investment factor, and a profitability factor, and show that the model outperforms the Fama and French three-factor model in explaining a set of well-known cross-sectional return patterns. Interestingly, they show that the investment factor is able to explain a large proportion of the value premium (low valuation firms do not invest a lot while high valuation firms invest a lot) and the profitability factor explains a sizable proportion of the momentum premium (momentum stocks correspond to highly profitable firms). They suggest using their four-factor model as a better alternative to the Carhart four-factor model or Fama and French's three-factor model and stress the economic grounding of the investment and profitability factors.

Lyandres, Sun, and Zhang (2008) test a two-factor model (market factor and investment factor) and a four factor model (market, size, value, and investment). They show that adding the investment factor into the CAPM and the Fama and French three-factor model is useful in the context of explaining widely documented anomalies related to equity issuance.

Fama and French (2014) propose a five factor model using the market factor, the small cap factor, the value factor and an investment and profitability factor. Importantly, they show that the value factor is redundant in the presence of the profitability and investment factor. Despite its redundancy they argue that the value factor should be included as it is a widely used and well-understood factor in investment practice. They argue that inclusion of the size factor is empirically important despite the fact that it cannot be justified through the dividend discount model that motivates the other factors. Interestingly (but without providing any empirical test), Fama and French argue that the

1. High Profitability and Low Investment as Factors

five-factor model should only be applied to portfolios which have a beta close to one as it does not capture the "betting against beta" (i.e. low risk) factor.

In the table below we report summary statistics of the five factors documented in Fama and French (2014). In panel A of the table, note that the monthly return on all five factors (market, size, value, profitability and investment) is positive over last 50 years (July 1963 - December 2013) and is statistically significant. Over this period, the average monthly return on the investment and the profitability factor is positive (0.17% and 0.22%) and are statistically significant (at a 95% confidence interval), with t-statistics of 2.79 and 3.72.

Exhibit 4: Summary statistics of factors (Source: Fama and French, 2014)
Panel A of the table reports the average of monthly factor returns and their t-statistics. The market factor is the return on all sample stocks minus the 1-month US Treasury bill rate. The size, value, profitability and investment factors are created as returns on small minus large capitalisation portfolios, high minus low book-to-market portfolios, high minus low operating profitability portfolios and low minus high asset growth portfolios, respectively. The value, profitability and investment factors are constructed after controlling for size. All portfolios are value weighted. The period and sample for analysis is July 1963 to December 2013 and the firms are incorporated in the USA and listed on NYSE, AMEX or NASDAQ. Panel B reports correlation between the five factors. We refer readers to Fama and French (2014) for a detailed description of the construction of the five factors presented here.

Panel A: Summary Statistics					
	Market	Size	Value	Profitability	Investment
Average monthly return (in %)	0.5	0.3	0.28	0.17	0.22
t-statistics	2.74	2.33	3.22	2.79	3.72
Panel B: Correlation between Factors					
	Market	Size	Value	Profitability	Investment
Market	1	0.3	-0.34	-0.13	-0.43
Size		1	-0.16	-0.32	-0.13
Value			1	0.04	0.71
Profitability				1	-0.19
Investment					1

Exhibit 5 shows the Carhart four-factor regression results for long/short portfolios formed by sorting on high-profitability and low-investment scores. The long leg has the highest 30% profitable firms and the short leg has the lowest 30% profitable firms in the case of profitability score and the long leg has the lowest 30% investment firms and the short leg has the highest 30% investment firms in the case of investment score. It can be observed that for both long legs of the factors the alphas are significant at the 95% confidence level. Also, their exposures, particularly to the HML factor, are quite different, which is in line with our earlier argument about treating the two characteristics (High Profitability and Low Investment) as independent factors.

1. High Profitability and Low Investment as Factors

Exhibit 5: Empirical Evidence of High Profitability and Low Investment Factors – Carhart 4-Factor Regression of Long/Short Portfolios
All statistics are annualised. The analysis is based on daily total return data from 31 December 1973 to 31 December 2013 (40 years). All portfolios are constructed using the underlying universe of the largest 500 US stocks. The Low Investment score is obtained using the 2-Year total asset growth rate. The High Profitability score is obtained using the Gross Profit/Total Assets ratio. Regression stats with p-values < 5% are highlighted in bold and alphas are annualised. The Market factor is the return on cap-weighted portfolio of all stocks in the Scientific Beta LTTR USA universe over risk-free rate. SMB/HML/MOM factors are long/short cap-weighted portfolios of long small- cap stocks (in the broad market)/30% highest book-to-market/30% past 12M-1M highest return stocks and short the 30% largest cap stocks/30% lowest book-to-market/30% past 12M-1M lowest return stocks in the Scientific Beta LTTR USA universe.

Carhart Betas of Portfolios (CW) based on Firm Characteristic Scores (40 years)				
Betas	Low Investment		High Profitability	
	Long (30%)	Short (30%)	Long (30%)	Short (30%)
Alpha	**1.81%**	**-1.31%**	**2.43%**	**-2.65%**
Market Beta	**0.91**	**1.11**	**0.97**	**1.04**
SMB Beta	**0.03**	**0.04**	0.00	0.00
HML Beta	**0.12**	**-0.14**	**-0.36**	**0.51**
MOM Beta	**0.04**	**-0.04**	0.00	**-0.06**
R-square	91.80%	96.00%	95.23%	94.13%

1. High Profitability and Low Investment as Factors

2. Smart Factor Indices for High Profitability and Low Investment Tilts

2. Smart Factor Indices for High Profitability and Low Investment Tilts

We have discussed the reasoning and the evidence for the premium associated with the two factors – high profitability and low investment. In this section we describe how ERI Scientific Beta constructs its smart factor indices, which allow investors to gain exposure to these rewarded risk factors. We will also discuss the historical performance of these indices.

2.1. Scientific Beta Multi-Strategy Factor Indices

ERI Scientific Beta uses a consistent smart beta index-design framework for the construction of its smart factor indices known as the Smart Beta 2.0 approach. In this approach to index construction, the selection and weighting phases are clearly separated, which enables investors to choose the risks to which they do or do not wish to be exposed. A well-diversified weighting scheme provides efficient access to the risk premia associated with this factor exposure. The idea is to construct an investable proxy for the risk factor (beta) chosen while reducing unrewarded risks through the use of a well-diversified weighting scheme.

Such an ex-ante methodological framework for constructing a portfolio is a tool for avoiding the trap of constructing ad-hoc methodologies that only perform well in the back-test. All the available variations (or choices) provided within the framework are based on proven academic or applied research, allowing flexibility to accommodate various investor preferences. Moreover, publishing a wide range of indices that correspond to variations within a given index design framework allows investors to assess the sensitivity of each index construction strategy to the model specification choices.

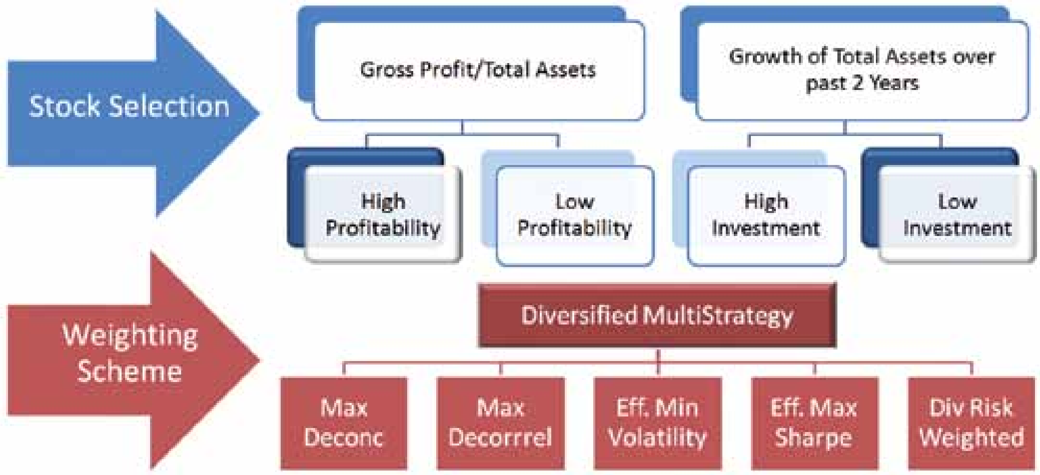
Exhibit 6: Overview of Smart Beta

Exhibit 7 depicts the detailed phases of the Smart Beta 2.0 approach in constructing the profitability and investment smart factor indices. In the stock selection phase the broad stock universe, after applying sufficient investability filters, is divided into two halves based on the characteristic proxy variables – Gross Profitability (Gross Profit/Total Assets) in the case of the Profitability factor and Total Asset Growth over two years in the case of the Investment factor. Then the 50% of stocks tilting towards the rewarded factor tilt are selected (High Profitability and Low Investment) in the stock selection phase. For strategic reasons and to allow more flexibility for asset managers to use the factor indices as building blocks for their portfolios for any short-term gains, low profitability and high investment indices are also constructed. Once the stock selection is done, five different weights are computed for each stock using the five diversification weighting schemes used in the Scientific Beta framework: Maximum Deconcentration, Maximum Decorrelation, Efficient

2. Smart Factor Indices for High Profitability and Low Investment Tilts

Minimum Volatility, Efficient Maximum Sharpe Ratio and Diversified Risk Weighting. In order to minimise strategy-specific risks that may arise due to the weighting scheme, further diversification is provided by equal weighting the weights computed by the five weighting schemes resulting in the diversified multi-strategy index.

Exhibit 7: High Profitability and Low Investment Smart Factor Multi-Strategy Index Construction - Overview



Scientific Beta has been a strong advocate of transparency in the index construction process, enabling independent third parties to replicate the index performance if they desire to do so. Exhibit 8 gives a detailed overview of all the steps involved in the index construction process. The stocks are selected based on the score of the proxy variable, such as Asset Growth over two years and Gross Profitability. The scores are calculated annually in June. The portfolio rebalancing takes place every quarter with checks for investability such as turnover and liquidity control. The index values are calibrated daily using daily returns of stocks and multifactor allocation is done quarterly coinciding with the rebalancing of individual component single factor indices. Every quarter, the two factor indices (profitability and investment) are equal weighted to obtain the multi-factor indices.

Exhibit 8: High Profitability and Low Investment Smart Factor Multi-Strategy Index Construction - Details

Scoring	Annually (in June)	All stocks in the regional universe are assigned two factor scores: • Asset Growth Score: Past 2-year growth rate of Total Assets • Gross Profitability Score: Gross Profit to Total Assets Ratio
Stock Selection	Quarterly	• 50% stocks with lowest Asset Growth Score are selected as Low Investment • 50% stocks with highest Gross Profitability Score are selected as High Profitability stocks
Portfolio Optimisation	Quarterly	Diversified Multi-Strategy weighting is applied to each stock selection followed by ex-post weight constraints to ensure de-concentration.
Rebalancing	Quarterly	**Turnover Control:** The portfolio is not rebalanced until the turnover resulting from optimal weights reaches a pre-estimated threshold level. **Liquidity Control:** 1) Weight of each stock is capped to avoid large investment in the smallest stocks 2) The change in weight of each stock is capped to avoid large trading in small illiquid stocks.
Valuation	Daily	Portfolio valuation is done using quarterly weights and daily stock returns, which results in Low Investment and High Profitability ***smart factor indices***.
Multi-Factor Allocation	Quarterly	An equal-weighted allocation across Low Investment and High Profitability smart factor indices is performed to obtain a custom LI + HP combination.

2. Smart Factor Indices for High Profitability and Low Investment Tilts

2.2. Analytics

2.2.1. Performance Analysis

Absolute and relative performance statistics of high profitability and low investment factor multi-strategy indices as well as cap-weighted indices for USA long term data are presented in Exhibit 9.[2] It can be seen that the returns and Sharpe Ratio of both cap-weighted and multi-strategy indices for profitability and investment factors are higher than for the broad cap-weighted benchmark. However, the smart-weighted multi-strategy indices outperform the corresponding cap-weighted factor index by a big margin. The low investment multi-strategy index has a return of 15.18% and a Sharpe Ratio of 0.64, whereas the cap-weighted low investment index has a return of 12.91% and a Sharpe Ratio of 0.47. Similarly, the high profitability multi-strategy index has a return of 14.31% and a Sharpe Ratio of 0.56, whereas the cap-weighted high profitability index has a return of 11.25% and a Sharpe Ratio of 0.34.

Most importantly, both low investment and high profitability multi-strategy indices show statistically significant outperformance over the broad cap-weighted benchmark. The outperformance is a result of two phenomena acting in parallel. Firstly, some outperformance is derived from simply tilting towards the stocks with rewarded systematic risk, i.e. the documented premium of Low Investment and High Profitability factors. Secondly, the diversified weighting scheme further improves performance due to diversification of unrewarded risks. Other absolute statistics such as the Sortino Ratio are also significantly better for the multi-strategy indices with respect to the cap-weighted factor indices, and in turn better than the broad cap-weighted benchmark.

In the relative analytics, the low investment multi-strategy index has a tracking error of 5.61% and an Information Ratio of 0.75, whereas the cap-weighted low investment index has a tracking error of 3.95% and an Information Ratio of 0.50. Similarly, the high profitability multi-strategy index has a tracking error of 4.48% and an Information Ratio of 0.75, whereas the cap-weighted high profitability index has a tracking error of 3.39% and an Information Ratio of 0.09. The five-year probability of outperformance of both multi-strategy indices is greater than 85%.

2 - The Scientific Beta US Long-Term Track Records are based on stocks that are members of the S&P 500 universe and are alive at the cut-off day. The benchmark used is the total market-cap-weighted portfolio of all stocks. These track records are updated yearly, on 15 May of year (y+1) for the end of year (y). At the time that this study was published, the most recent long-term track records available were those from 2013.

2. Smart Factor Indices for High Profitability and Low Investment Tilts

Exhibit 9: Performance Analysis of High Profitability and Low Investment Smart Factor Indices
All statistics are annualised. Yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. The analysis is based on daily total return data from 31 December 1973 to 31 December 2013 (40 years). Scientific Beta LTTR Low Investment portfolios are constructed on the 50% of stocks with the lowest 2-Year total asset growth rate in the USA universe. Scientific Beta LTTR High Profitability portfolios are constructed on the 50% of stocks with the highest Gross Profit/Total Assets ratio in the USA universe. The benchmark is the cap-weighted portfolio of all stocks in the US universe. The Scientific Beta LTTR USA universe consists of the 500 largest US stocks. P-values of paired sample t-tests are reported where the underlying null hypothesis is that the sample returns of the benchmark and that of the strategy come from distributions with equal means. Less than 5% p-value denotes that the average return of the strategy is significantly different from the average return of the benchmark, i.e. the outperformance is significant with 95% statistical confidence. Probability of outperformance is the probability of obtaining positive excess returns if one invests in the strategy for a period of 3 (or 1) years at any point during the history of the strategy. Rolling window of 3 (or 1) year length and a step size of 1 week is used.

US Long-Term (Dec-1973 to Dec-2013)	All Stocks CW	Low Investment CW	Low Investment Multi-Strategy	High Profitability CW	High Profitability Multi-Strategy
Absolute Analytics					
Annual Returns	10.95%	12.91%	15.18%	11.25%	14.31%
Annual Volatility	17.38%	16.22%	15.50%	17.40%	16.13%
Sharpe Ratio	0.32	0.47	0.64	0.34	0.56
Sortino Ratio	0.46	0.66	0.89	0.48	0.78
Relative Analytics					
Annual Relative Returns	-	1.96%	4.23%	0.29%	3.36%
P-value of Outperformance	-	1.26%	0.01%	61.72%	0.01%
Tracking Error	-	3.95%	5.61%	3.39%	4.48%
Information Ratio	-	0.50	0.75	0.09	0.75
Outperformance Probability (1Y)	-	63.85%	72.64%	50.93%	70.58%
Outperformance Probability (3Y)	-	75.16%	81.21%	56.94%	82.40%
Outperformance Probability (5Y)	-	87.58%	88.51%	62.31%	87.64%
5% Relative Returns	-	-5.50%	-9.11%	-6.52%	-6.22%
95% Tracking Error	-	6.89%	10.06%	6.75%	7.58%

2.2.2. Drawdown Analysis

Exhibit 10 presents the maximum drawdown of the profitability and investment smart factor indices for US long-term track records. It can be seen that the maximum drawdowns of factor-tilted indices are lower than those of the broad CW benchmark and the time to recover the loss is also less for the factor-tilted indices. Concerning the maximum loss on a relative basis with respect to the benchmark, the cap-weighted indices suffer less relative loss compared to the multi-strategy indices, owing to the cap-weighting being similar to that of the benchmark. However, the maximum time to recover the loss is much smaller for the multi-strategy indices compared to their respective cap-weighted indices.

The profitability and investment smart factor indices show reduction in absolute extreme risk, measured using CF 5% VaR, compared to both their tilted CW indices and the broad CW index. Relative extreme risk (relative to broad CW), measured using the CF 5% VaTER of both smart factor indices, is slightly higher than that of tilted CW indices. This observation is justified by the de-concentrating nature of the weighting scheme used for constructing smart factor indices. In other words, the tilted CW indices have lower tracking error and lower CF 5% VaTER because their underlying weighting brings them closer to the broad CW index.

2. Smart Factor Indices for High Profitability and Low Investment Tilts

Exhibit 10: Drawdown Analysis of High Profitability and Low Investment Smart Factor Indices
The analysis is based on daily total return data from 31/12/1973 to 31/12/2013 (40 years). The benchmark is the cap-weighted portfolio of all stocks in the Scientific Beta LTTR US universe. Maximum drawdown represents the maximum loss an investor can suffer from investing in the strategy at the highest point and selling at the lowest. It is the largest single drop from peak to bottom in the value of a portfolio (before a new peak is achieved). Maximum relative drawdown is the maximum drawdown of the long/short index whose return is given by the fractional change in the ratio of the strategy index to the benchmark index. The Cornish-Fisher VaR is computed using the Cornish-Fisher extension that adjusts the VaR for the presence of asymmetry (i.e. skewness) and/or heavy tails (i.e. excess kurtosis) in the return distribution. VaR is based on historical returns and measures the possibility of maximum daily loss. The level of 5% means that there is only a 5% chance that the strategy will experience a daily loss that is greater than the reported loss. The Cornish-Fisher VaTER is similar to the Cornish-Fisher VaR except that it provides the worst expected loss of the strategy relative to the CW benchmark. The Scientific Beta LTTR US universe consists of the 500 largest US stocks.

US Long Term (Dec-1973 to Dec-2013)	All Stocks CW	Low Investment CW	Low Investment Multi-Strategy	High Profitability CW	High Profitability Multi-Strategy
Absolute Analytics					
Maximum Drawdown	54.53%	53.38%	53.20%	52.29%	48.28%
Maximum Time Under Water	1595	1141	935	2802	856
Start of Max Time Under Water	04-Sep-00	16-Jul-99	04-Jun-07	27-Mar-00	13-Jul-07
End of Max Time Under Water	13-Oct-06	01-Dec-03	03-Jan-11	22-Dec-10	25-Oct-10
Cornish Fisher 5% VaR (daily)	1.51%	1.39%	1.33%	1.50%	1.41%
Relative Analytics					
Max Relative Drawdown	-	26.47%	38.49%	20.27%	25.21%
Max Relative Time Under Water	-	2083	1944	6345	1837
Start of Max Relative Time Under Water	-	18-Apr-94	25-Mar-94	13-Jun-74	21-Nov-94
End of Max Relative Time Under Water	-	11-Apr-02	06-Sep-01	08-Oct-98	05-Dec-01
Cornish Fisher 5% VaTER (daily)	-	0.38%	0.53%	0.32%	0.43%

2.2.3. Conditional Performance Analysis

Exhibit 11 presents the conditional performance analysis of US long-term profitability and investment smart factor indices. The low investment multi-strategy index outperforms by 2.63% and 6.03% in bull and bear markets respectively. The low investment CW index outperforms by just 0.21% in bull and 4.12% in bear markets. The high profitability multi-strategy index has an outperformance of 3.62% and 2.75% in bull and bear markets respectively. Its CW counterpart underperforms in bull markets (-0.08%) and delivers 0.76% in bear markets, showing a clear inclination towards bear markets.

It is essential to analyse the conditional performance to assess the robustness of weighting schemes. It is clear that investment and profitability multi-factor indices tend to provide more balanced outperformance across different market conditions compared to the tilted cap-weighted indices.

2. Smart Factor Indices for High Profitability and Low Investment Tilts

Exhibit 11: Conditional Performance Analysis of High Profitability and Low Investment Smart Factor Indices
Calendar quarters with positive market index returns comprise bull markets and the rest constitute bear markets. All statistics are annualised. The analysis is based on daily total return data from 31/12/1973 to 31/12/2013 (40 years). The Scientific Beta LTTR US universe consists of the 500 largest US stocks. The benchmark is the cap-weighted portfolio of all stocks in the US universe.

US Long Term (Dec-1973 to Dec-2013)	Low Investment CW	Low Investment Multi-Strategy	High Profitability CW	High Profitability Multi-Strategy
Bull Markets				
Annual Relative Returns	0.21%	2.63%	-0.08%	3.62%
Tracking Error	3.32%	4.80%	2.88%	3.94%
Information Ratio	0.06	0.55	-0.03	0.92
Bear Markets				
Annual Relative Returns	4.12%	6.03%	0.76%	2.75%
Tracking Error	5.08%	7.09%	4.32%	5.52%
Information Ratio	0.81	0.85	0.18	0.50

2.2.4. Factor Exposure

Exhibit 12 presents the results of the Carhart four-factor model regression of the profitability and investment factor indices for US long term track records. Both the cap-weighted and multi-strategy indices for the profitability and investment factors have statistically significant alpha. This shows that the profitability and investment factor premia are not fully explained by the other factors such as market, value, size and momentum. However, there is small but significant exposure to the other factors as the factors are correlated with each other (details on correlations can be found in Section 3 of this paper).

The low investment and high profitability smart factor indices both have SMB beta in the range 0.16-0.19, which is a result of moving away from cap weighting i.e. de-concentration due to the diversified multi-strategy weighting scheme. It is important to note that the low investment smart factor index has a positive exposure to the HML factor (0.16) and low market beta (0.87) while the high profitability smart factor index has a negative exposure (-0.08) and higher market beta of 0.93. Overall, the two smart factor indices add value relative to the standard Carhart factors and are quite different from each other.

Exhibit 12: Carhart Four-Factor Model Regression
Regression statistics with p-values < 5% are highlighted in bold and alphas are annualised. The yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. The analysis is based on daily total return data from 31 December 1973 to 31 December 2013 (40 years). The Scientific Beta LTTR Low Investment portfolios are constructed on the 50% of stocks with the lowest 2-Year total asset growth rate in the US universe. The Scientific Beta LTTR High Profitability portfolios are constructed on the 50% of stocks with the highest Gross Profit/Total Assets ratio in the US universe. The Scientific Beta LTTR US universe consists of the 500 largest US stocks .The Market factor is the cap-weighted portfolio of all stocks over the risk-free rate. The SMB/HML/MOM factors are long/short cap-weighted portfolios that are long small-cap stocks (in the broad market)/30% highest book-to-market/30% past 12M-1M highest return stocks and short the 30% largest cap stocks/30% lowest book-to-market/30% past 12M-1M lowest return stocks in the Scientific Beta LTTR US universe.

Dec 1973 – Dec 2013 (40 Years)	Scientific Beta USA Long Term Track Records				
	All Stocks	Low Investment		High Profitability	
	Cap-Weighted	Cap-Weighted	Multi-Strategy	Cap-Weighted	Multi-Strategy
Annualised Alpha	-	**1.45%**	**2.82%**	**1.71%**	**3.14%**
Market Beta	**1**	**0.91**	**0.87**	**0.99**	**0.93**
SMB Beta	-	**-0.02**	**0.16**	0.00	**0.19**
HML Beta	-	**0.12**	**0.16**	**-0.25**	**-0.08**
MOM Beta	-	**0.04**	**0.04**	**0.01**	**-0.01**
R-squared	100.00%	95.50%	92.90%	98.56%	95.11%

2. Smart Factor Indices for High Profitability and Low Investment Tilts

2.2.5. Investability

Issues relating to high turnover and capacity are usually held up as arguments against factor investing. The results of a recent survey conducted by EDHEC-Risk Institute shows that investors are concerned about the implementation constraints of smart beta strategies.

Exhibit 13 shows a summary of findings of the EDHEC-Risk Alternative Equity Beta Survey conducted as part of the Newedge "Advanced Modelling for Alternative Investments" research chair at EDHEC-Risk Institute (Badaoui et al., 2015).[3] Survey participants were provided with a list of potential reasons as to why they would not invest in smart beta strategies and were asked to rate these from 1 to 5, with 1 being the weakest reason and 5 being the strongest for not choosing smart beta investment strategies. As can be seen from Exhibit 13, the survey reveals that "Issues related to turnover and capacity" (with an average score of 3.23 out of 5) is the second most important reason why investors are reluctant to choose smart beta strategies, just after robustness concerns.

Exhibit 13: Summary of EDHEC Risk Alternative Equity Beta Survey conducted as part of the Newedge "Advanced Modelling for Alternative Investments" research chair at EDHEC-Risk Institute

Reasons for not Investing in Smart Beta Strategies	Average Score
Doubts over robustness of outperformance	3.62
Issues related to turnover and capacity	3.23
Limited information on risks	3.10
Limited availability of independent research	2.97
Limited availability of data	2.87
High licensing fees	2.82
Insufficient explanation of concepts behind offerings	2.76
Low transparency of rules	2.60
Insufficient number of offerings	2.40

Turnover rules and liquidity rules are applied to smart factor indices to overcome the problems of high turnover and limited capacity. Within the Scientific Beta index construction process, adjustments are performed with the aim of ensuring the investability of our indices, either by reducing and controlling turnover-related costs, or by allowing their liquidity profile to be improved in a systematic, robust and transparent fashion. A conditional rebalancing approach is used that avoids unnecessary rebalancing unless a significant amount of new information has been received since the last index rebalancing, hence avoiding rebalancing due to noise. The capacity constraints allow us to manage the deviations from the cap-weighted reference index in terms of individual stock market capitalisation both at the trading and the holding levels.[4]

To foster more liquidity, investors have the option of making a highly liquid stock selection on top of the existing factor-tilted selection. These indices are constructed on the most liquid 70% of stocks among the selected stocks and are called "high liquidity smart factor indices." High profitability and low investment smart factor indices, constructed within the consistent smart factor index construction framework, are also subject to the investability checks.

3 - Badaoui, S., F. Goltz, V. Le Sourd and A. Lodh. 2015. Alternative Equity Beta Investing: A Survey. EDHEC-Risk Institute Publication (forthcoming).
4 - The target for smart factor indices is 30% 1-way annual turnover. For more information on turnover and liquidity rules, please refer to the white paper "Overview of Diversification Strategies" by Gonzalez and Thabault (2013).

2. Smart Factor Indices for High Profitability and Low Investment Tilts

Exhibit 14 shows that the capacity of both standard smart factor indices is sufficiently high at \$10.2bn and \$14.0bn, compared to \$47.4bn for the broad CW index. The 'Highly Liquid' filter improves capacity drastically (\$14.5bn and \$20.8bn respectively). The impact of the high liquidity filter on performance is marginal – outperformance is reduced from 4.23% to 3.61% for the low investment smart factor index, and from 3.36% to 2.58% for the high profitability smart factor index. The annual one-way turnovers of the low investment and high profitability smart factor indices are 31.8% and 22.2% respectively. Two levels of transaction costs are used to obtain a more realistic estimate of the impact of trading on outperformance in practice: - 20 bps per 100% 1-W turnover and 100 bps per 100% 1-W turnover (extreme scenario).[5] The excess returns net of transaction costs are still quite significantly high – 3.27% and 2.34% for highly-liquid low investment and highly-liquid high profitability smart factor indices respectively.

Exhibit 14: Investability of High Profitability and Low Investment Smart Factor Indices
All statistics are annualised. Yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. The analysis is based on daily total return data from 31 December 1973 to 31 December 2013 (40 years). The Scientific Beta LTTR Low Investment Diversified Multi-Strategy portfolios are constructed on the 50% of stocks with the lowest 2-Year total asset growth rate in the US universe. The Scientific Beta LTTR High Profitability Diversified Multi-Strategy portfolios are constructed on the 50% of stocks with the highest Gross Profit/Total Assets ratio in the US universe. The High Liquidity filter selects (over the existing selection) the top 60% stocks by past liquidity. The Scientific Beta LTTR US universe consists of the 500 largest US stocks. The benchmark is the cap-weighted portfolio of all stocks in the US universe. The effective number of stocks (ENS) is defined as the reciprocal of the Herfindahl Index, which is defined as the sum of squared weights across portfolio constituents. Mean Capacity is the weighted average market capitalisation of the index in \$million.

Dec 1973 – Dec 2013 (40 Years)	Scientific Beta Long Term Track Records Multi-Strategy				
	All Stocks	Standard		Highly Liquid Selection	
	Cap-Weighted	Low Invest.	High Profit.	Low Invest.	High Profit.
Effective Number	115	189	200	117	123
Capacity (\$million)	47,381	10,216	14,032	14,499	20,814
Ann. 1-Way Turnover	2.67%	31.80%	22.23%	33.96%	24.08%
Information Ratio	-	0.75	0.75	0.72	0.65
Ann. Relative Returns	-	4.23%	3.36%	3.61%	2.58%
Net Returns (20 bps)	-	4.16%	3.31%	3.55%	2.53%
Net Returns (100 bps)	-	3.91%	3.13%	3.27%	2.34%

2.2.6. Performance Analysis of Scientific Beta Investable Indices

Finally, we present a performance and risk snapshot for the Scientific Beta low investment and high profitability smart factor indices in six different developed regions – Eurozone, UK, Japan, Developed Asia Pacific ex Japan, Developed ex US, and Developed. Scientific Beta investable indices are constructed using price and fundamentals data from the CIQ database. It is these indices that constitute the investable reference offered by Scientific Beta. The long-term track records used previously serve as a basis for long-term performance and risk analyses that are useful for qualifying the robustness and economic and statistical significance of the performances of the strategy.[6]

For Scientific Beta investable indices, the eligibility of securities is decided by i) the stock exchange, ii) the type of instrument and iii) the issue date. In each Scientific Beta universe, a liquidity screen is applied and the top securities by free-float market-cap are selected. The liquidity screen is

5 - 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.
6 - The Scientific Beta US Long-Term Track Records are based on stocks that are members of the S&P 500 universe and are alive at the cut-off day. The benchmark used is the total market-cap-weighted portfolio of all stocks. These track records are updated yearly, on 15 May of year (y+1) for end of year (y). At the time that this study was published, the most recent long-term track records available were those from 2013.

2. Smart Factor Indices for High Profitability and Low Investment Tilts

governed by a score which is the average of the 'trading ratio' (TR) z-score and the 'average traded daily dollar volume' (ATDDV) z-score. TR and ATDDV are median values over the last four quarters.[7] All remaining strategy construction rules, including turnover and liquidity rules, remain the same as detailed in section 2.1. Due to reasons of data availability, all analytics are based on daily total returns over the latest 10-year period.

Exhibit 15 shows that low investment and high profitability smart factor indices post high outperformance numbers across all geographies. The outperformance of the Scientific Beta low investment smart factor index ranges from 2.32% in Japan to 3.94% in the UK, and that of the Scientific Beta high profitability smart factor index ranges from 1.47% in Dev Asia Pacific ex Japan to 5.23% in the UK. For Developed World, the Scientific Beta low investment smart factor index exhibits an information ratio of 0.97 and an outperformance probability (3Y) of 100%, while the Scientific Beta high profitability smart factor index respectively posts 0.98 and 98.36% for these indicators.

Exhibit 15: Performance of Low Investment/High Profitability- Multi-Strategy Indices for Scientific Beta Developed Regions
All statistics are annualised. The analysis is based on daily total return data from 31 December 2004 to 31 December 2014 (10 years) in EUR for the Eurozone, GBP for the UK, JPY for Japan, and USD for Developed Asia Pacific ex Japan, Developed ex US and Developed. The benchmark is the cap-weighted portfolio of all stocks in the respective Scientific Beta region. Calendar quarters with positive market index returns comprise bull markets and the rest constitute bear markets. Regression stats with p-values < 5% are highlighted in bold and alphas are annualised. The effective number of stocks (ENS) is defined as the reciprocal of the Herfindahl Index, which is defined as the sum of squared weights across portfolio constituents. Mean Capacity is the weighted average market capitalisation of the index in $million. The risk-free rate used in the Eurozone is Euribor (3M), in the UK is UK T-Bill (3M), in Japan is Gensaki T-Bill (1M), and in other regions is the Secondary Market US T-bill (3M). The number of stocks in each region is 300, 100, 500, 400, 1,500 and 2,000 respectively.

Dec 2004 – Dec 2014 (10 Years)	Scientific Beta Low Investment Diversified Multi-Strategy Index					
	Eurozone	UK	Japan	Dev Asia Pac ex Japan	Developed ex US	Developed
Sharpe Ratio	0.34	0.53	0.31	0.58	0.41	0.53
Ann. Rel. Returns	2.54%	3.94%	2.32%	3.17%	2.82%	2.87%
Tracking Error	5.75%	6.79%	6.53%	6.93%	3.79%	2.98%
Information Ratio	0.44	0.58	0.36	0.46	0.74	0.97
Outperf Prob. (3Y)	82.79%	84.43%	72.68%	89.07%	100.00%	100.00%
Annual Alpha	2.24%	3.65%	1.85%	**3.47%**	**2.37%**	**2.85%**
Market Beta	**0.88**	**0.87**	**0.90**	**0.87**	**0.91**	**0.90**
SMB Beta	**0.10**	**0.11**	**0.12**	**0.22**	**0.17**	**0.11**
HML Beta	-0.01	**-0.07**	**0.06**	**0.13**	0.01	**-0.02**
MOM Beta	**0.07**	**-0.03**	**0.14**	**0.05**	**0.06**	**0.03**
Bull Markets						
Relative Returns	2.05%	0.92%	-6.39%	-0.43%	1.09%	1.89%
Tracking Error	4.28%	5.49%	5.14%	5.44%	2.64%	2.07%
Information Ratio	0.48	0.17	-1.24	-0.08	0.41	0.91
Bear Markets						
Relative Returns	2.79%	7.17%	6.94%	6.66%	4.15%	3.61%
Tracking Error	8.03%	8.99%	7.94%	9.85%	5.47%	4.57%

7 - For more information on the construction rules for the Scientific Beta investable universe, please refer to the white paper – Scientific Beta Global Developed Universe, available at www.scientificbeta.com.

2. Smart Factor Indices for High Profitability and Low Investment Tilts

Information Ratio	0.35	0.80	0.87	0.68	0.76	0.79
Effective Number	112	41	191	143	415	549
Capacity ($mill)	13,061	23,852	5,993	5,067	13,590	19,547
Ann. 1-Way T/O	41.08%	41.35%	38.59%	38.59%	42.54%	40.06%
Net Returns (20 bps)	2.45%	3.85%	2.25%	3.09%	2.73%	2.79%
Net Returns (100 bps)	2.13%	3.52%	1.94%	2.78%	2.39%	2.47%

Dec 2004 – Dec 2014 (10 Years)	Scientific Beta High Profitability Diversified Multi-Strategy Index					
	Eurozone	UK	Japan	Dev Asia Pac ex Japan	Developed ex US	Developed
Sharpe Ratio	0.41	0.61	0.36	0.50	0.44	0.55
Ann. Rel. Returns	3.31%	5.23%	3.09%	1.47%	3.35%	3.11%
Tracking Error	6.54%	6.07%	6.95%	6.69%	3.79%	3.17%
Information Ratio	0.51	0.86	0.45	0.22	0.88	0.98
Outperf. Prob. (3Y)	95.36%	99.73%	89.89%	95.36%	100.00%	98.36%
Annual Alpha	**3.62%**	**4.13%**	**3.52%**	2.43%	**3.08%**	**3.08%**
Market Beta	**0.91**	**0.91**	**0.87**	**0.86**	**0.93**	**0.95**
SMB Beta	**0.10**	**0.10**	**0.12**	**0.24**	**0.17**	**0.18**
HML Beta	**-0.24**	**-0.20**	**-0.05**	**0.02**	**-0.09**	**-0.17**
MOM Beta	**-0.02**	**-0.04**	**0.06**	**0.04**	**0.04**	0.00
Bull Markets						
Relative Returns	0.20%	2.74%	-9.25%	-1.86%	1.51%	1.45%
Tracking Error	5.55%	4.97%	6.18%	5.34%	3.08%	2.45%
Information Ratio	0.04	0.55	-1.50	-0.35	0.49	0.59
Bear Markets						
Relative Returns	6.29%	8.30%	10.61%	5.45%	4.93%	5.03%
Tracking Error	8.29%	7.93%	7.83%	9.42%	4.98%	4.55%
Information Ratio	0.76	1.05	1.36	0.58	0.99	1.10
Effective Number	118	41	204	143	405	530
Capacity ($mill)	12,575	27,559	5,399	4,633	14,672	23,945
Ann. 1-Way T/O	26.16%	26.70%	26.12%	30.11%	28.19%	27.26%
Net Returns (20 bps)	3.26%	5.18%	3.04%	1.41%	3.29%	3.05%
Net Returns (100 bps)	3.05%	4.96%	2.83%	1.17%	3.07%	2.84%

2. Smart Factor Indices for High Profitability and Low Investment Tilts

3. Combining High Profitability and Low Investment Factors

3. Combining High Profitability and Low Investment Factors

As discussed earlier, high profitability and low investment are two distinct factors, each with their own risk characteristics and each carrying their own individual risk premium supported by the academic literature.

Given that multi-factor models typically use separate factors for investment and profitability, there does not seem to be any reason to consider them as related variables representing the same factor. In fact, considering that the investment and profitability variables should be used together is as well-founded as considering for example that the value and size variables or the value and momentum variables should be combined within a single factor. In fact, if there is any evidence supporting combinations of variables within one factor, it is argued (see in particular Novy-Marx 2013) that profitability can be used as an additional variable within a value factor. Based on this, one could consider profitability as an additional screen within a value stock selection. Many commercial indices marketed under the umbrella of 'quality' indices do not make a distinction between the low investment and high profitability factors. Instead they use a composite of a wide range of scores. Most of them do not comply with either factor.[8]

Exhibit 16 tabulates the correlation of various factors, including profitability and investment, over a 40-year horizon. It can be observed that the profitability and investment factors are negatively correlated (-0.14), further strengthening our argument that they are indeed two entirely different risk factors. They are not the proxies for the same systematic risk, as is the case with the value risk factor, where fundamental variables such as book-to-market and earnings-to-price are both proxies for the same underlying risk factor, which is value. Therefore, the low investment and high profitability factors cannot be combined in a composite manner to represent a single risk factor. However, owing to their low correlation with other factors and with each other, they are good candidates for multi-factor allocations.

There is strong intuition suggesting that multi-factor allocations will tend to result in improved risk-adjusted performance. In fact, even though the factors to which the factor indices are exposed are all positively rewarded over the long term, there is extensive evidence that they may each encounter prolonged periods of underperformance. More generally, the reward for exposure to these factors has been shown to vary over time (see e.g. Harvey (1989); Asness (1992); Cohen, Polk and Vuolteenaho (2003)). If this time variation in returns is not completely in sync for different factors, allocating across factors allows investors to diversify the sources of their outperformance and smooth their performance across market conditions. In short, the cyclicality of returns differs from one factor to the other, i.e. the different factors work at different times. Intuitively, we would expect pronounced allocation benefits across factors which have low correlation with each other.

8 - The MSCI Quality Index uses ROE, Debt-to-Equity and Earnings Variability; the Russell Quality HEFI index uses ROA, Debt-to-Equity and Earnings Variability; and the S&P 500 High Quality Ranking index uses Growth and Stability of Earnings and Recorded Dividends to compute the Quality score of stocks.

3. Combining High Profitability and Low Investment Factors

Exhibit 16: Correlation of Various Factors
The analysis is based on daily total return data from 31 December 1973 to 31 December 2013 (40 years). The SMB/HML/MOM factors are long/short cap-weighted portfolios that are long small-cap stocks (in the broad market)/30% highest book-to-market/30% past 12M-1M highest return stocks and short the 30% largest cap stocks/30% lowest book-to-market/30% past 12M-1M lowest return stocks respectively in the Scientific Beta LTTR US universe. The Low Investment/High Profitability factors are long/short cap-weighted portfolios that are long the 30% lowest 2-Year total asset growth/30% highest Gross Profitability stocks and short the 30% highest 2-Year total asset growth/30% lowest Gross Profitability stocks respectively in the Scientific Beta US universe. The Scientific Beta LTTR US universe consists of the 500 largest US stocks.

Correlations of Long/Short Factors	SMB Factor	HML Factor	MOM Factor	Investment Factor	Profitability Factor
SMB Factor	1	0.31	-0.07	0.15	-0.23
HML Factor		1	-0.33	0.24	-0.81
MOM Factor			1	0.08	0.35
Investment Factor				1	-0.14
Profitability Factor					1

Exhibit 17 shows the percentage of overlap of stocks among various stock selections over a 40-year horizon. From the broad US universe of 500 stocks, each factor index has 250 securities and Exhibit 17 shows the percentage of stocks out of 250 that is shared between factor index universes. It can be seen that the low investment and high profitability factors share around 44% of stocks. This corresponds to 110 stocks that are common between the low investment and high profitability factor indices. This number is not very different from that of other factor indices such as value, size and momentum, each of which shares roughly 50% of the stocks (see table).

The low level of overlap, in conjunction with the negative correlations between the two factors observed previously, once again shows that low investment and high profitability are two different risk factors. Additionally, as there are so few stocks that are common between the two factors, the combination of the two factor indices will also lead to improved stock level diversification due to the increased number of securities.

Exhibit 17: Overlap across Factor Indices in terms of Percentage of Shared Stocks
The analysis is based on portfolio holdings between the period March 1974 and December 2013 (40 years/160 quarters). The Scientific Beta LTTR US Mid-Cap selection is constructed on the 50% of stocks with the lowest market capitalisation. The Scientific Beta LTTR US Value selection is constructed on the 50% of stocks with the highest B/M ratio. The Scientific Beta LTTR US High Momentum selection is constructed on the 50% of stocks with the highest past 12M-1M returns. The Scientific Beta LTTR US Low Investment selection is constructed on the 50% of stocks with the lowest 2-Year total asset growth rate. The Scientific Beta LTTR US High Profitability selection is constructed on the 50% of stocks with the highest Gross Profitability. The score-based classification of stocks is conducted annually in June. The Scientific Beta LTTR US universe consists of the 500 largest US stocks.

Overlap (% of Stocks)	Mid Cap	Value	High Momentum	Low Investment	High Profitability
Mid-Cap	100%	57%	47%	55%	51%
Value		100%	50%	58%	30%
High Momentum			100%	51%	51%
Low Investment				100%	44%
High Profitability					100%

3. Combining High Profitability and Low Investment Factors

3.1. Scientific Beta Long Term Track Records for Custom EW Combination of Low Investment and High Profitability

Given the low correlation between low investment and high profitability, which are often considered to be representative of the same quality factor, we thought that it would be interesting to be able to present the results of an EW combination of these indices. Consequently, in this sub-section, we present the back-tested performance of the quarterly rebalanced customised multi-factor (EW) index using Scientific Beta US Long-Term Track Records (with 40 years of history).

Exhibit 18 shows the benefit of an equal-weighted combination of the two smart factor indices and compares it with the stand-alone results of its component indices. The custom index has significant outperformance over the broad cap-weighted index of its component indices. The customised multi-factor (EW) index has low volatility and a Sharpe ratio of 0.60, which is close to the average of the Sharpe ratios of the single factor investment and profitability indices.

The benefit of factor diversification can be seen in the relative performance panel. The customised multi-factor index posts a tracking error (4.66%) that is lower than the average of its components. Consequently, the information ratio of the customised multi-factor index (EW) (0.82) is higher than that of the two component single factor indices (0.75 each). This benefit does not come at the cost of any higher order risk (like VaR and VaTER) or deeper drawdown. The drawdown and Value-at-Risk (both absolute and relative) of the customised multi-factor (EW) index are the same as those of its component indices. It is clear that there is a diversification benefit to combining the single factor indices into a multi-factor index.

Exhibit 18: Performance of Low Investment/High Profitability- Multi-Strategy Indices and Profitability and Investment Single Factor Indices
All statistics are annualised. The yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. The analysis is based on daily total return data from 31 December 1973 to 31 December 2013 (40 years). The Scientific Beta LTTR Low Investment Diversified Multi-Strategy index is constructed on the 50% of stocks with the lowest 2-Year total asset growth rate in the US universe. The Scientific Beta LTTR High Profitability Diversified Multi-Strategy index is constructed on the 50% of stocks with the highest Gross Profit/Total Assets ratio in the US universe. The EW customised index is an equal-weighted combination of the Scientific Beta LTTR Low Investment Multi-Strategy and Scientific Beta LTTR High Profitability Multi-Strategy indices, rebalanced quarterly. The score-based classification of stocks is conducted annually in June. The Scientific Beta LTTR US universe consists of the 500 largest US stocks .The benchmark is the cap-weighted portfolio of all stocks in the US universe. P-values of paired sample t-tests are reported where the underlying null hypothesis is that the sample returns of the benchmark and that of the strategy come from distributions with equal means. 5% p-value denotes that the average return of the strategy is significantly different from the average return of the benchmark, i.e. the outperformance is significant with a 95% statistical confidence level. The Cornish-Fisher VaR is computed using the Cornish-Fisher extension that adjusts the VaR for the presence of asymmetry (i.e. skewness) and/or heavy tails (i.e. excess kurtosis) in the return distribution. VaR is based on historical returns and measures the possibility of maximum daily loss. The level of 5% means that there is only a 5% chance that the strategy will experience a daily loss that is greater than the reported loss. The Cornish-Fisher VaTER is similar to the Cornish-Fisher VaR, except that it provides the worst expected loss of the strategy relative to the CW benchmark.

Dec 1973 – Dec 2013 (40 Years)	Scientific Beta USA Long-Term Track Records			
	Broad Cap-Weighted	Low Investment Multi-Strategy	High Profitability Multi-Strategy	Custom EW Combination
Absolute Analytics				
Annual Returns	10.95%	15.18%	14.31%	14.78%
Annual Volatility	17.38%	15.50%	16.13%	15.69%
Sharpe Ratio	0.32	0.64	0.56	0.60
Max Drawdown	54.53%	53.20%	48.28%	50.75%
Cornish Fisher 5% VaR (daily)	1.51%	1.33%	1.41%	1.35%

3. Combining High Profitability and Low Investment Factors

Relative Analytics				
Ann. Rel. Returns	-	4.23%	3.36%	3.83%
P-value of Outperformance	-	0.01%	0.01%	0.00%
Tracking Error	-	5.61%	4.48%	4.66%
Information Ratio	-	0.75	0.75	0.82
Max Rel. Drawdown	-	38.49%	25.21%	31.39%
Cornish Fisher 5% VaTER (daily)	-	0.53%	0.43%	0.43%

3.2. Custom Combination of Scientific Beta Low Investment and High Profitability Investable Indices

Having seen the long-term track records in US markets, it is equally important to access the performance of the same strategy in other developed markets. Therefore, in this sub-section, we show key performance and risk indicators for Scientific Beta investable indices in six different developed regions – Eurozone, UK, Japan, Developed Asia Pacific ex Japan, Developed ex US, and Developed. It is important to recall that the Scientific Beta investable indices are constructed using price and fundamentals data from the CIQ database. For Scientific Beta investable indices, a liquidity screen is applied and the top securities by free-float market-cap are selected. All remaining strategy construction rules, including turnover and liquidity rules, remain the same as detailed in section 2.1. Due to reasons of data availability, all analytics are based on daily total returns in the latest 10-year period.

In a manner similar to that of US track records, strong outperformance is observed in other developed regions as well. The excess returns range from 2.34% In Dev Asia Pacific ex Japan to 4.61% in the UK. All Scientific Beta customised multi-factor (EW) indices show high information ratios and high outperformance probabilities. Notably, the Scientific Beta Developed customised multi-factor (EW) index has an information ratio of 1.06 and 100% outperformance probability.

The customised multi-factor (EW) indices across all regions exhibit significant positive Carhart alpha and they are defensive overall, i.e. they all have a market beta that is less than one (0.86-0.92). They all possess positive SMB beta and, with the exception of Dev Asia Pacific ex Japan, they all have zero to negative exposure to the HML factor. Due to their defensive nature, their out-performance (over the broad CW index) is better in bear markets than in bull markets.

3. Combining High Profitability and Low Investment Factors

Exhibit 19: Performance of Low Investment/High Profitability- Multi-Strategy Indices for Scientific Beta Developed Regions
All statistics are annualised. The analysis is based on daily total return data from 31 December 2004 to 31 December 2014 (10 years) in EUR for Eurozone, GBP for the UK, JPY for Japan, and USD for Developed Asia Pacific ex Japan, Developed ex US and Developed. The EW customised index is an equal-weighted combination of the Scientific Beta Low Investment Diversified Multi-Strategy and Scientific Beta High Profitability Diversified Multi-Strategy indices in each region, rebalanced quarterly. The benchmark is the cap-weighted portfolio of all stocks in the respective Scientific Beta region. P-values of paired sample t-tests are reported where the underlying null hypothesis is that the sample returns of the benchmark and that of the strategy come from distributions with equal means. 5% p-value denotes that the average return of the strategy is significantly different from the average return of the benchmark, i.e. the outperformance is significant with a 95% statistical confidence level. Calendar quarters with positive market index returns comprise bull markets and the rest constitute bear markets. Regression stats with p-values < 5% are highlighted in bold and alphas are annualised. The risk-free rate used in the Eurozone is Euribor (3M), in the UK is the UK T-Bill (3M), in Japan is the Gensaki T-Bill (1M), and in other regions is the Secondary Market US T-bill (3M). The number of stocks in each region is 300, 100, 500, 400, 1,500 and 2,000 respectively.

Dec 2004 – Dec 2014 (10 Years)	Scientific Beta Customised Multi-Factor (EW) Index					
	Eurozone	UK	Japan	Dev Asia Pac ex Japan	Developed ex US	Developed
Sharpe Ratio	0.38	0.58	0.34	0.54	0.43	0.54
Ann Rel. Returns	2.96%	4.61%	2.75%	2.34%	3.09%	3.00%
P-value of Outperformance	25.08%	4.89%	35.52%	55.89%	2.99%	0.55%
Tracking Error	5.72%	6.07%	6.40%	6.52%	3.61%	2.84%
Information Ratio	0.52	0.76	0.43	0.36	0.86	1.06
Outperf. Prob. (3Y)	95.90%	96.17%	88.80%	94.81%	100.00%	100.00%
Annual Alpha	**2.94%**	**3.89%**	**2.70%**	**2.95%**	**2.73%**	**2.97%**
Market Beta	**0.89**	**0.89**	**0.88**	**0.86**	**0.92**	**0.92**
SMB Beta	**0.10**	**0.10**	**0.12**	**0.23**	**0.17**	**0.14**
HML Beta	**-0.13**	**-0.14**	0.01	**0.08**	**-0.04**	**-0.10**
MOM Beta	**0.03**	**-0.03**	**0.10**	**0.04**	**0.05**	**0.02**
Bull Markets						
Relative Returns	1.15%	1.85%	-7.79%	-1.12%	1.31%	1.68%
Tracking Error	4.52%	4.86%	5.31%	5.10%	2.70%	2.04%
Information Ratio	0.25	0.38	-1.47	-0.22	0.49	0.82
Bear Markets						
Relative Returns	4.55%	7.77%	8.79%	6.07%	4.55%	4.33%
Tracking Error	7.69%	8.09%	7.56%	9.33%	5.03%	4.31%
Information Ratio	0.59	0.96	1.16	0.65	0.90	1.00

4. Comparison of Industry Offerings

4. Comparison of Industry Offerings

Many commercial index providers who claim to harvest the high profitability and low investment factor premia through their indices market them under the category of "Quality" indices. In this section, the index construction methodology and the performance of a few industry offerings such as the MSCI Quality Index, the Russell High Efficiency (HEFI) Quality Index, the FTSE Quality Index and the S&P 500 High Quality Ranking Index are compared with those of Scientific Beta indices.

4.1. Methodology Comparison

This section presents a comparative analysis of the index construction methodology of the competitors such as MSCI, Russell and S&P. Exhibit 20 summarises the construction methodology of the competitors' "quality" indices.

It must be noted that competitors mix a systematic approach to stock picking (alpha) with criteria used to define beta. For example, scoring stocks by a combination of a return on equity (ROE) score and an earnings variability score could be a good criterion if the objective is stock picking. However, reward for systematic risk does not exist for a combination of scores, meaning that making stock selection based on a composite score does not tilt the portfolio to either beta. It selects stocks that are ranked moderately in both scores and therefore do not necessarily represent either of the systematic risks. This approach is therefore confusing and does not capture all possible risk premia, an example being the absence of any variable that explicitly provides exposure to the investment factor.

The competing "quality" indices use a quality score to weight the portfolio in a variety of ways, ranging from using the quality score to tilt the market-cap portfolio (MSCI approach), and converting quality scores into active weights using a probability algorithm (Russell approach), to weighting stocks in proportion to their quality scores (S&P approach). Irrespective of the definition of quality, ignoring stock correlations in the weighting leads to a less diversified portfolio, which in turn results in inferior performance. We previously discussed the possibilities of data mining when using such non-standard proprietary definitions and ad-hoc mixtures of proxy variables, further questioning the robustness of future performance. Scientific Beta indices stick to the consistent index methodology used to construct smart factor indices, as described in section 2.1, allowing for separate high profitability and low investment factors and thus capturing the two factor premia separately with smart weighting offering better diversification.

Exhibit 20: Index Construction Methodology Comparison of Competitors

Index	Variables Used	Scoring Criteria	Portfolio Construction
MSCI Quality Index	• Return on Equity • Debt-to-Equity • Earnings Variability	Compute average of 3 z-scores.	Select top stocks by Quality score to target 30% market cap.
Russell Quality (HEFI) Index	• Return On Assets • Debt-to-Equity • Earnings Variability	Compute scores for each of 3 variables using NLP algorithm. Use mean composite score.	Convert composite scores[9] into *active weights* (over CW) using NLP algorithm.

9 - The scoring criterion results in exclusion of approximately 50% stocks from the parent index.

4. Comparison of Industry Offerings

FTSE Quality Index	• Δ Asset Turnover • Accruals • Leverage Ratio[10]	Compute *Profitability* z-score (mean across 3 z-scores) and *Leverage* z-score.	Construct broad factor index. Construct narrow factor index by removing stocks that contribute least to the Quality factor.
S&P 500 High Quality Ranking Index	• Earnings Growth • Earnings Stability • Dividends	Select *High Quality Rankings* stocks from parent index. Assign Quality Rank scores.	Weight stocks by QR Score.

4.2. Performance Comparison

This section presents a comparative analysis of the performance of ERI Scientific Beta's high profitability factor index, low investment factor index and the custom equal-weighted index of the two factor indices along with the equivalent "quality" indices from some competitors such as MSCI, Russell and S&P. Exhibit 21 shows the absolute and relative return and risk of all the Scientific Beta and competitor indices. As can be seen from the table, the annual returns and Sharpe ratio based on the 10-year historical data of Scientific Beta indices are higher than those of its competitors. Comparing the custom equal-weighted multi-factor index with the competitors' "quality" indices is a fair comparison as each of them uses the profitability or investment measures, or both, as screening criteria in their methodology, as discussed in the previous section.

On comparing the relative performance with respect to the broad market indices (the S&P 500 index and the MSCI World index), Scientific Beta indices have a very high information ratio compared to that of its competitors. In the US, the custom multi-factor (EW) index has an information ratio of 0.83, which is higher than that of the competitor indices (MSCI USA Quality Index – 0.30; Russell 1000 Quality (HEFI) – 0.59; S&P 500 High Quality Rankings – 0.03). It is also worth noting that the outperformance probability based on a 3-year time horizon is 98.9% on the basis of the 10-year historical period. In the Developed region, Scientific Beta's custom multi-factor (EW) index beats competitors both in terms of relative returns (+3.14%) and in terms of information ratio (0.96).

Exhibit 21: Performance Comparison of Scientific Beta and its Competitors (Panel A: US, Pane B: Developed)
All statistics are annualised. The yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. The analysis is based on daily total return data from 31 December 2004 to 31 December 2014 (10 years). Probability of outperformance is the probability of obtaining positive excess return returns if one invests in the strategy for a period of 3 years at any point during the history of the strategy. A rolling window of 3-year length and 1-week step size is used.
Panel A: The S&P 500 Index is used as the broad cap-weighted benchmark. The EW customised index is an equal-weighted combination of the Scientific Beta US Low Investment Multi-Strategy and Scientific Beta US High Profitability Diversified Multi-Strategy indices, rebalanced quarterly. The Scientific Beta US universe consists of 500 stocks.

Dec 2004 – Dec 2014 (10 Years)	S&P 500 Index	Scientific Beta USA			Competitors USA		
		Low Investment Multi-Strategy	High Profitability Multi-Strategy	Custom EW Combination	MSCI USA Quality Index	Russell 1000 Quality (HEFI)	S&P 500 High Quality Rankings
Absolute Analytics							
Ann. Returns	7.65%	10.88%	10.59%	10.75%	9.05%	9.50%	7.79%
Ann. Volatility	20.39%	18.81%	18.75%	18.70%	18.12%	19.34%	20.52%
Sharpe Ratio	0.30	0.50	0.49	0.50	0.42	0.42	0.31
Max Drawdown	55.25%	50.82%	47.58%	48.95%	44.03%	48.61%	57.68%

10 - All profitability and leverage measures are calculated relative to the relevant regional median stock level. For financial firms, ROA is the only measure of quality.

4. Comparison of Industry Offerings

Relative Analytics							
Ann. Rel. Returns	-	3.23%	2.94%	3.10%	1.40%	1.85%	0.14%
Tracking Error	-	3.72%	4.45%	3.74%	4.65%	3.12%	4.81%
Information Ratio	-	0.87	0.66	0.83	0.30	0.59	0.03
Outperf .Prob. (3Y)	-	100.00%	91.80%	98.91%	83.33%	90.71%	62.84%

Panel B: The MSCI World Index is used as the broad cap-weighted benchmark. The EW customised index is an equal-weighted combination of the Scientific Beta Developed Low Investment Multi-Strategy and Scientific Beta Developed High Profitability Diversified Multi-Strategy indices, rebalanced quarterly. The Scientific Beta Developed universe consists of 2,000 stocks.

Dec 2004 – Dec 2014 (10 Years)	MSCI World Index	Scientific Beta Developed			Competitors Developed		
		Low Investment Multi-Strategy	High Profitability Multi-Strategy	Custom EW Combination	MSCI World Quality Index	Russell Dev Quality (HEFI)	FTSE Developed Quality
Absolute Analytics							
Ann. Returns	6.59%	9.60%	9.84%	9.73%	8.95%	8.73%	8.29%
Ann. Volatility	17.49%	15.31%	15.39%	15.31%	16.77%	16.90%	16.07%
Sharpe Ratio	0.29	0.53	0.55	0.54	0.45	0.43	0.43
Max Drawdown	57.46%	51.47%	49.98%	50.70%	48.01%	52.70%	49.51%
Relative Analytics							
Ann. Rel. Returns	-	3.01%	3.25%	3.14%	2.36%	2.14%	1.70%
Tracking Error	-	3.46%	3.46%	3.26%	4.24%	2.60%	2.87%
Information Ratio	-	0.87	0.94	0.96	0.56	0.82	0.59
Outperf Prob. (3Y)	-	100.00%	99.18%	99.73%	92.90%	94.54%	90.16%

Exhibit 22 presents the results of a Carhart four-factor model regression for Scientific Beta's high profitability and low investment indices and its competitors' "quality" indices. The statistically significant coefficients are highlighted in bold. In the US, with the exception of the S&P 500 quality index, all other indices have statistically significant alpha, which implies that their excess returns are not entirely explained by the other four factors. The Russell 1000 Quality (HEFI) index has a market beta close to 1, while the Scientific Beta custom multi-factor (EW) index is the most defensive, with a market beta of 0.92. All indices have negative exposure to the HML factor. The MSCI USA Quality index has negative SMB beta while all others have positive SMB exposure.

In Developed, all indices show significant alpha, with that of Scientific Beta's custom multi-factor (EW) index being the highest (+3.24%). The MSCI and Russell indices have high market beta while the Scientific Beta and FTSE indices are more defensive. The only common trait among these indices is strongly negative exposure to the HML factor.

4. Comparison of Industry Offerings

Exhibit 22: Carhart Four-Factor Model Regression Summary (Panel A: USA, Panel B: Developed)
Regression statistics with p-values < 5% are highlighted in bold and alphas are annualised. The yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. The analysis is based on daily total return data from 31 December 2004 to 31 December 2014 (10 years).
Panel A: The EW customised index is an equal-weighted combination of the Scientific Beta USA Low Investment Multi-Strategy and Scientific Beta USA High Profitability Diversified Multi-Strategy indices, rebalanced quarterly. The Scientific Beta US universe consists of 500 stocks. The Market factor is the returns of the S&P 500 index over the risk-free rate. The SMB/HML/MOM factors are long/short cap-weighted portfolios that are long small-cap stocks (in the broad market)/30% highest book-to-market/30% past 12M-1M highest return stocks and short the 30% largest cap stocks/30% lowest book-to-market/30% past 12M-1M lowest return stocks in the Scientific Beta US universe.

Dec 2004 – Dec 2014 (10 Years)	S&P 500 Index	Scientific Beta USA			Competitors USA		
		Low Investment Multi-Strategy	High Profitability Multi-Strategy	Custom EW Combination	MSCI USA Quality Index	Russell 1000 Quality (HEFI)	S&P 500 High Quality Rankings
Annualised Alpha	-	**3.19%**	**2.93%**	**3.06%**	**1.98%**	**1.76%**	0.51%
Market Beta	**1.00**	**0.90**	**0.94**	**0.92**	**0.96**	**0.98**	**0.93**
SMB Beta	-	**0.10**	**0.15**	**0.13**	**-0.03**	**0.10**	**0.12**
HML Beta	-	**-0.03**	**-0.22**	**-0.13**	**-0.28**	**-0.17**	**-0.03**
MOM Beta	-	**0.04**	**0.02**	**0.03**	**-0.04**	**0.03**	**-0.17**
R-squared	100.0%	97.5%	97.7%	98.2%	97.8%	99.1%	96.3%

Panel B: The EW customised index is an equal-weighted combination of the Scientific Beta Developed Low Investment Multi-Strategy and Scientific Beta Developed High Profitability Diversified Multi-Strategy indices, rebalanced quarterly. The Scientific Beta Developed universe consists of 2,000 stocks. The Market factor is the returns of the MSCI World index over the risk-free rate. Other risk factors are prepared for each Scientific Beta developed regional building block and are aggregated using the region's market-cap weights. In each Scientific Beta developed regional building block, the SMB/HML/MOM factors are long/short cap-weighted portfolios that are long small-cap stocks (in the broad market)/30% highest book-to-market/30% past 12M-1M highest return stocks and short the 30% largest cap stocks/30% lowest book-to-market/30% past 12M-1M lowest return stocks in the corresponding universe.

Dec 2004 – Dec 2014 (10 Years)	MSCI World Index	Scientific Beta Developed			Competitors Developed		
		Low Investment Multi-Strategy	High Profitability Multi-Strategy	Custom EW Combination	MSCI World Quality Index	Russell Dev Quality (HEFI)	FTSE Developed Quality
Annualised Alpha	-	**3.12%**	**3.35%**	**3.24%**	**2.72%**	**1.92%**	**2.07%**
Market Beta	**1.00**	**0.89**	**0.94**	**0.91**	**1.00**	**1.02**	**0.97**
SMB Beta	-	**0.08**	**0.16**	**0.12**	-0.02	**0.16**	**-0.03**
HML Beta	-	**-0.05**	**-0.21**	**-0.13**	**-0.22**	**-0.20**	**-0.18**
MOM Beta	-	**0.04**	0.01	**0.02**	-0.01	**0.02**	**0.02**
R-squared	100.0%	97.6%	98.6%	98.6%	95.1%	99.0%	98.8%

Exhibit 23 below shows the conditional performance analysis of the Scientific Beta indices and the competitors. The performance of the indices during bull and bear markets is presented separately for a better understanding of the risk and return of these indices. In the US, the MSCI and S&P 500 quality indices produce negative returns with respect to the S&P 500 broad cap-weighted index during the bull markets and a positive relative return during the bear markets. Although the Russell 1000 Quality index provides positive returns for both bull and bear market conditions relative to the broad cap-weighted benchmark, the magnitude is much smaller compared to the Scientific Beta indices. The Scientific Beta custom multi-factor (EW) index has more balanced outperformance in both regimes than its competitors and is thus more robust to changing market conditions.

4. Comparison of Industry Offerings

In developed markets also, both the MSCI World Quality Index and the FTSE Developed Quality Index show strong dependence on market conditions. The Scientific Beta custom multi-factor (EW) index once again produces outperformance in both bull and bear markets.

Exhibit 23: Conditional Performance Analysis of Scientific Beta and its Competitors (Panel A: US, Pane B: Developed)
All statistics are annualised. The yield on Secondary US Treasury Bills (3M) is used as a proxy for the risk-free rate. The analysis is based on daily total return data from 31 December 2004 to 31 December 2014 (10 years). Calendar quarters with positive market returns are bull quarters and the rest are bear quarters.
Panel A: The S&P 500 index is used as the broad cap-weighted benchmark. The EW customised index is an equal-weighted combination of the Scientific Beta US Low Investment Multi-Strategy and Scientific Beta USA High Profitability Diversified Multi-Strategy indices, rebalanced quarterly. The Scientific Beta US universe consists of 500 stocks.

Dec 2004 – Dec 2014 (10 Years)	Scientific Beta USA			Competitors USA		
	Low Investment Multi-Strategy	High Profitability Multi-Strategy	Custom EW Combination	MSCI USA Quality Index	Russell 1000 Quality (HEFI)	S&P 500 High Quality Rankings
Bull Markets						
Ann. Rel. Returns	1.85%	1.63%	1.75%	-1.74%	0.80%	-0.95%
Tracking Error	2.77%	3.39%	2.74%	3.41%	2.28%	3.43%
Information Ratio	0.67	0.48	0.64	-0.51	0.35	-0.28
Bear Markets						
Ann. Rel. Returns	4.54%	4.36%	4.46%	5.39%	2.87%	1.91%
Tracking Error	5.46%	6.50%	5.56%	6.94%	4.68%	7.31%
Information Ratio	0.83	0.67	0.80	0.78	0.61	0.26

Panel B: The MSCI World index is used as the broad cap-weighted benchmark. The EW customised index is an equal-weighted combination of the Scientific Beta Developed Low Investment Multi-Strategy and Scientific Beta Developed High Profitability Diversified Multi-Strategy indices, rebalanced quarterly. The Scientific Beta Developed universe consists of 2,000 stocks.

Dec 2004 – Dec 2014 (10 Years)	Scientific Beta Developed			Competitors Developed		
	Low Investment Multi-Strategy	High Profitability Multi-Strategy	Custom EW Combination	MSCI World Quality Index	Russell Dev Quality (HEFI)	FTSE Developed Quality
Bull Markets						
Ann. Rel. Returns	1.94%	1.49%	1.72%	-1.94%	1.32%	-1.07%
Tracking Error	2.46%	2.65%	2.35%	3.48%	1.94%	2.10%
Information Ratio	0.79	0.56	0.73	-0.56	0.68	-0.51
Bear Markets						
Ann. Rel. Returns	3.81%	5.23%	4.53%	8.02%	2.79%	5.11%
Tracking Error	5.26%	5.03%	4.93%	5.77%	3.84%	4.28%
Information Ratio	0.72	1.04	0.92	1.39	0.73	1.19

Conclusion

Conclusion

Recent empirical studies document the role of two separate factors related to firm characteristics: low investment and high profitability. These factors rely on straightforward and parsimonious indicators, and can be expected to provide more robust performance benefits than ad-hoc stock picking indicators of "quality" used in the industry. This view of the two factors as separate factors is also reflected in the economic explanation for each factor, which does not particularly link the factors together. Moreover, early empirical work documenting the existence of a risk premium associated with each factor has typically focused on one of the two factors while ignoring the other one, in a similar way to that in which the small-cap, value and momentum premia were first documented. Therefore, both factors seem to have a similar standing as potential sources of systematic risk and thus an associated reward. In fact, this avoids the risk of data-mining inherent in ad-hoc stock ranking methods. The performance of factor-tilted indices can be improved by the use of a diversification-based weighting scheme, such as the diversified multi-strategy scheme offered by Scientific Beta. Further value can be added by allocating across these two factors. Such allocations notably exploit the low correlation of factor returns across the two factors. Such combinations of the smart factor indices for high profitability and low investment have led to improved performance compared to various commercial indices which are based on ad-hoc definitions of "quality."

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- Smart Factor Indices (January).
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