Smart Beta ETFs

- Smart Investment or Smart Marketing?

A study of equity investment and weighting schemes

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Abstract

Smart Beta is a relatively new investment strategy that builds further on theses such as factor investing and fundamental indexation. As of now, there are conflicting views of this strategy. Hence, in this paper, we aim to find an answer to whether Smart Beta is indeed smart or not.

When comparing the returns of Smart Beta ETFs to the returns of passive benchmarks, we find that no Smart Beta ETF category outperforms. However, when regressing Smart Beta ETFs against mutual funds, we find that Smart Beta in fact could be a disruptive innovation for active management. In addition, when added as a complement to a self-constructed portfolio, consisting of 60% equity and 40% bonds, 38% of Smart Beta ETFs actually contributed positively to the performance of the portfolio.

Investing in a single Smart Beta ETF would hence not be a better course of action than investing in a passive index fund. However, Smart Beta ETFs as a complement or a combination of Smart Beta ETFs might enable you to achieve greater returns. In that way, Smart Beta may be more than just smart marketing.

Keywords: Smart Beta, ETFs, Factor Investing, Portfolio Management, Fundamental Indexation

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1 Introduction

Smart Beta, Strategic Beta, Fundamental Indexation or Factor Investing? Different titles addressing the same topic. Smart Beta, hereafter referred to as SB, is in essence the use of weighting schemes other than traditional cap-weighting in order to avoid downsides of the latter (Arnott, 2014). One shortcoming of cap-weighting an index is that it can make the index hold large positions in overpriced stocks and small positions in underpriced stocks (Hsu, 2006). A SB index is therefore constructed based on factors that differ from market capitalization, such as Fundamentals, Volatility and Momentum, to name a few. This is in order to (1) enhance returns, (2) improve diversification and (3) reduce risk, and to a lower cost than active investment (Agather, 2016).

Arnott (2005), the pioneer in this field, presented already in 2005 what he claimed was proof that SB indeed is a great investment strategy. He constructed a portfolio based on fundamental indices. The results were that of outperformance over the S&P 500 over 43 years.

Andrew Ang (2016) also talks in favor of Smart Beta. He describes his view of the strategy like this: "*Factors are the languages of investing that everyone should be speaking. Smart Beta is the vehicle to deliver factor investing".* Numbers in surveys show that this message has been retrieved among investors. When FTSE Russell conducted their third SB survey in 2016, figures revealed that the use of SB is on the upswing. 72% of the survey respondents were using or actively evaluating SB indices, an increase of 28% from the year beforehand (Agather, 2016). In fact, during these four months that we have conducted our thesis, the number of SB Exchange-Traded Funds (ETFs) on the daily updated website ETF.com has risen from 795 to 889, an increase of nearly 12%.

That said, as much recommendation there is to invest in SB products, just as much skepticism is there. Burton Malkiel, economist professor at Princeton, remains reluctant. The underlying message in his article is that trying to beat the market is a fool's errand. The best you can do is investing in a cap-weighted portfolio (Malkiel, 2014). Furthermore, the title of an article in Financial Times states quite clearly the magazine's point of view: "*Smart Beta is no guarantee that you will beat the market*". Surveying 5 of the 10 biggest SB ETFs tracking the US market, their conclusion was that the SB ETFs underperformed a cap-weighted benchmark over 5 years (Evans, 2015).

Given these divergent opinions about the SB strategy, it would be interesting to examine the strategy more thoroughly. Hence, in this paper we aim to find an answer to whether SB products are indeed smart or not. The first comprehensive study of this kind was carried out by Denys Glushkov who looked into US-domiciled SB ETFs. He concluded his paper by stating that no SB ETF outperformed their risk-adjusted benchmark (Glushkov, 2014). In order to make a statement of our own, we need to get into the depth of the concept of Smart Beta. As Jacobs and Levy (2014) put it: "*When considering any active strategy, whether smart beta or smart alpha, investors should have a clear understanding of the sources of expected returns, the stability and sustainability of those returns, the risk exposures and risk controls, the strategy's liquidity demands, and whether the management costs are commensurate with expected results. Only then can investors determine which strategies deserve the "smart" label.*" Which is why we will proceed by taking the following steps:

First, we investigate whether SB ETFs generate abnormal returns on a risk-adjusted basis when compared to their benchmark. Second, we also test if SB ETFs generate a positive alpha over Fama French Carhart factors, as well as how much of any potential return that can be explained by these factors. Third, to find out if SB is a disruptive innovation for active management, we examine the performance of mutual funds and hedge funds against several SB ETF strategies combined. Fourth, we end our analysis by exploring whether SB ETFs contribute positively as a complement to a passive portfolio, consisting of 60% equity and 40% bonds, rather than on a stand-alone basis.

Previous studies of SB have been focusing on specific markets, the US for instance (Glushkov (2014, Arnott (2005)). These readings suggest that further research should include extending the market. Thus, we aim to analyze the whole market of SB ETFs when regressing SB ETFs against their benchmarks. This is our first contribution to existing research within this subject.

A second input will be the comparison of SB ETFs returns to the returns of Fama French Carhart factors. This is a generally accepted method when evaluating funds but so far, we have not come across any research applying this exact method on SB. Glushkov (2014) evaluated SB ETFs against a blended benchmark, consisting of market, value and size factors, i.e. the Fama French 3-factor model. In our analysis, we add momentum and volatility to the mix. Hence, we apply the Fama French Carhart model, with the addition of volatility, hereafter referred to as FFC+V. The addition of volatility has its reasons in that we also investigate active strategies, such as hedge funds, which are supposed to perform better in bad times. A negative beta against this volatility factor would indicate a positive return in bad times, hence, volatility could be seen as a sort of reversed risk-factor.

A third add-on will be evaluating the performance of active strategies against SB. If it is indeed possible to combine SB ETFs to replicate the returns of active funds at a lower cost, then SB could be a disruptive innovation for active management.

Finally, investigating the active choice of SB as a complement to a passive portfolio of 60% equity and 40% bonds yields a fourth addition. Kahn and Lemmon (2015) argues that any typical investor should own SB products in addition to his/her active and passive placements. They state that this could generate higher cost-adjusted returns and/or lower risk. As it happens, SB ETFs are seldom held in isolation. They are rather held as a complement to standard equity indices and to long-only managers (Amenc, 2015). SB should hence not be examined only in isolation.

It seems to us that few have addressed these above mentioned issues. Indeed, a survey conducted in 2015 reveals that there is still substantial uncertainty regarding SB products, and challenges in evaluating it (Amenc, 2015). Hence, we believe our paper will make a desired contribution to today's research and meet some of the information needs regarding SB strategies.

We find that SB strategies deliver very low positive alphas, or even negative, when compared to their benchmarks. None of the categories produce an alpha above zero with a significance level of 95%. The Sharpe ratios are low or negative, and the information ratios (IRs) are either negative or very close to zero. When regressing against FFC+V factors, the results are somewhat similar.

However, adding a SB ETF to a portfolio of 60% equity and 40% bonds, reveals that 38% of the SB ETFs turn out to contribute positively to the Sharpe ratio. When regressing mutual funds against all SB strategies, we see that it could be possible to replicate mutual funds' performance by combining SB strategies. You might even gain a higher alpha at a lower cost. This result does not apply to hedge funds, though.

The outline of the remainder of this paper is as follows: Section 2 presents previous literature. Section 3 presents the sample and choice of method applied in this study. Section 4 analyzes the results obtained. Section 5 concludes the paper, provides limitations of our study as well as suggestions for further research.

2 Literature Review

2.1 Name and Meaning of Smart Beta

Smart Beta, Strategic Beta, Fundamental Indexing or Factor Investing? Arnott (2014) has emphasized that "*[SB] is fast becoming one of the most overused, ill-defined, and controversial terms in the modern financial lexicon.*" An appropriate definition and scope of the concept is therefore in place. According to Research Affiliates, SB indices use a different weighting scheme compared to traditional cap-weighted indices. Cap-weighted indices rely on price when determining how much of each stock to invest in. Had the market behaved according to the efficient market hypothesis (EMH), put forward by Eugene Fama (1965), this traditional approach would always be the ultimate strategy to go with. However, the SB strategies seek to draw an advantage from a supposed occasional inefficiency in the market. SB indices are constructed based on other factors rather than market capitalization, for instance Multi-factor, Growth and Value. This is in order to (1) enhance returns, (2) improve diversification and (3) reduce risk (Agather, 2016).

Towers Watson (2013), a leading global investment consulting firm who coined the term Smart Beta, uses the following updated definition: "*Smart Beta is simply about trying to identify good investment ideas that can be structured better [...] Smart Beta strategies should be simple, low cost, transparent and systematic.*" Arnott (2014) builds further on this definition by adding that SB is "*A category of valuation-indifferent strategies that consciously and deliberately break the link between the price of an asset and its weight in the portfolio, seeking to earn excess returns over the cap-weighted benchmark by no longer weighting assets proportional to their popularity, while retaining most of the positive attributes of passive indexing.*"

2.2. A branch of factor investing

A survey conducted by Blackrock (2016) pinpoints the fact that SB has its roots in factor investing and therefore is a new name behind an old concept. Kahn and Lemmon (2016) implies that SB strategies existed already in 1976, when Stephen Ross wrote a paper on arbitrage pricing theory (APT) and suggested that there was a relation between returns and various risk factors. Jacobs (2014) proposes further that the research about risk factors by Fama and French also has part in the origin of SB strategies. Fama and French (1993) found that the cross-section of average returns is only partly explained by the single-factor CAPM. Other factors that are not part of the CAPM proved to be able to explain more. They conducted a three-factor-model consisting of a market factor, a size factor and a value factor.

Hence, factors have played an important part when it comes to investment management for a long time. However, even though the underlying idea behind SB is not brand new, one part of the strategy is, namely, the characterizing feature of the strategy: it is now possible for the passive investor to capture returns in literally the same way that actively managed portfolios have before (Kahn, 2016). Through SB, factors help capture returns inexpensively, transparently and consistently in a passive portfolio.

2.2.1. Factor Definition

Factors are consequently a solid pillar on which the SB concept rests upon, and there are hundreds of them in the literature (Amenc, 2015). Bender (2013) explains her thoughts on factors: "*A factor can be thought of as any characteristic relating a group of securities that is important in explaining their return and risk."* With this wide definition, no wonder there are so many factors out there. John Cochrane (2011) describes the numerous quantity of factors as a zoo. To bring some clarity, Harvey et al. (2016) studied at least 316 factors. Through their findings, however, they concluded that only a handful of the factors were indeed statistically significant. Value, Low Volatility and Momentum were among the few factors proved to be very significant (Hsu, 2014).

A more selective definition of factors is therefore suitable. Hsu (2014) have named certain requirements when it comes to the characteristics regarding a factor for it to be viewed as, indeed, a factor. The factor must be "old" enough to have survived numerous database revisions. It must be present all over the globe, not change due to minor differences in the definition, probably be persistent in the future due to macro-risk exposure or a substantial behavioral bias and have a t-stat greater than 3.5.

Our decision of which factors to focus on was reached after a first analysis regarding time-series and the number of SB ETFs tilted towards each category[1]. This led us to evaluate Fundamentals, Multi-factor, Value, Momentum, Growth, Dividends, Low Volatility and Equal.

Using Fundamentals as a SB strategy is the same as weighting your portfolio on such things as gross revenue, equity book value cash flow and total employment etc. (Arnott, 2005). Fundamentals has experienced a drawback during recent years while Multi-factor and Value have been gaining more attention (Agather, 2016). Multi-factor is the strategy of combining different SB strategies and is said to provide you with the same diversification benefits as when investing in different assets (Bender, 2013). This diversification potential is then perhaps the reason for its popularity. Value focuses on stocks with low prices relative to their fundamental value.

[1] See section 4.2.

Momentum, the “Carhart factor”, was found to be a profitable strategy by Jegadeesh (2001). Momentum explains the difference between the monthly returns on diversified portfolios of the winners and losers of the past year (Carhart, 1997).

Growth focuses on high growth stocks and Dividends on stocks with higher than average dividend yields. Low Volatility is a strategy where you focus on stocks with lower than average volatility and Equal is the strategy of using equal weighting.

2.3 Active vs Passive

Given that SB indices use a different weighting scheme compared to traditional cap-weighted indices, there is a recurring discussion regarding if the strategy is passive or active. Some say SB is a hybrid investment strategy that lies somewhere between the two strategies (AlMahdi, 2015). Passive in a sense that the strategies are transparent, systematic and rules-based with the occasional need of rebalancing (Jacobs, 2014). Active in the way that they are seeking superior returns by another weighting scheme than cap-weighting. This forces you to make several active and subjective choices (Blitz, 2008). In particular, that is identifying the specific factors you wish to bet on as well as defining them (Jacobs, 2014).

Others argue that SB strategies should not be called hybrid strategies, but rather active strategies (Reilly, 2011). Asset owners themselves replied that 35% would put SB in the active categorization box whilst only 21% would choose the passive one (Agather, 2016). Bender (2013) views SB strategies as active management and states that they should then, like other active strategies, be judged against cap-weighted benchmarks. This is backed by a survey revealing that a majority of investors view cap-weighted indices as the benchmarks to assess the performance of SB strategies (Amenc, N. 2015).

However, active strategies are characterized by the involvement of a manager and his/her skill. SB, on the other hand, seeks to find superior returns thanks to its weighting scheme. Will this implicitly put it in the passive category? Jacobs and Levy (2014) argue that active managers have the potential to adjust for a range of issues that the SB strategy cannot. They say SB products are neither forward-looking nor dynamic and not well diversified, as opposed to active strategies. SB indices might furthermore experience unintended factor exposures, liquidity issues due to increased exposure to smaller-cap stocks, as well as overcrowding[2]. The transparency further tilts it towards the passive category (Jacobs, 2014). What's more, indexing in general is often viewed as a long-term buy-and-hold strategy, even though you once in a while need to rebalance the portfolio (Reilly, 2011). In terms of long-only, all of the SB ETFs we have analyzed so far are long-only strategies. This might have its reason in that investors feel like long/short strategies are too complex and that they need more knowledge about them before implementing them.

The most stressed argument for SB being a passive strategy, though, is that of targeting beta rather than alpha (Amenc, 2015). This implicitly leads us to consider whether the potential outperformance by SB strategies is to be viewed in terms of delivering alpha or beta. Glushkov (2014) explains that, if a potential abnormal return is compensation for assuming extra risk, then SB ETFs targets beta. However, if the abnormal return is a consequence of mispricing, then SB ETFs target alpha.

We stay indifferent to whether the SB strategy belongs to the passive or active investing type. We examine the performance of both passive and active funds, hence, a standpoint in this discussion is not needed. However, we will have a look into whether or not a potential abnormal return from SB strategies comes from assuming additional risk or mispricing. This is one of the most widely debated topics in the discussion of pros and cons about SB.

[2] Over-crowding is discussed below in section 2.4.2.

2.4 Proponents and Skepticism

The "smart" part of the SB name does not automatically indicate that alternative investment strategies such as cap-weighting is "dumb" (Arnott, 2014). However, Hsu (2006) points out that one of the downsides of traditional cap-weighting is that cap-weighting sometimes makes the index end up holding large positions in overpriced stocks and small positions in underpriced ones. Arnott (2005) demonstrates that their non-cap-weighted but fundamentals-weighted portfolio deliver higher returns and lower risks than traditional cap-weighted ones. Hsu (2014) delivered further evidence on the superiority of SB. He concludes that portfolios weighted in another manner than by market capitalization might outperform cap-weighted portfolios on a regular basis. When turning to asset owners themselves in 2016, 74% of them reported being "Satisfied" or "Very satisfied" with their SB allocations. This is an increase from 61% in 2015 (Agather, R. 2016).

2.4.1. Disruptive Innovation

SB might be viewed as somewhat of a disruptive innovation for active management. Many active managers charge an active fee for delivering higher returns through SB strategies. SB products are cheaper than actively managed products and so a high fee for active management should not be qualified for, if they achieve abnormal returns through SB (Kahn, 2016). In particular, hedge funds and mutual funds might essentially be a mixture of the different SB strategies. If it is indeed possible to combine SB ETFs to replicate the returns of these funds at a lower cost, then SB would be a disruptive innovation for active management.

2.4.2. Overcrowding

In recent years, though, Arnott himself (2016) has published a handful of articles addressing his concern that the increased popularity of SB ETFs might itself lead to a potential crash. He states: "*If the strong performance comes from structural alpha, terrific! If the performance is due to the strategy becoming more and more expensive relative to the market, watch out!*".

Malkiel (2014) is reluctant and even more sceptic than Arnott. He also warns about the over-exposure of SB funds and the risk of overcrowding. When too many investors aim for the same strategy or too many strategies aim for the same factor, it can cause the product to become overvalued. Overvaluation reduces or even eliminates any potential outperformance. This insight about factor crowding can lead to large withdrawals from SB strategies and a selling pressure as result. A crash would be the result.

2.4.3. Risk

Another argument against SB is the risk-level, that affects the interpretation of returns even though they are superior in relation to cap-weighted indices (Malkiel, 2014). The returns of SB strategies are not necessarily abnormal once risk is adjusted. Malkiel argues that the SB strategy merely delivers superior returns by assuming additional risk. How one measures risk is then a critical issue. Traditionally, beta is seen as a measure of risk and the higher the beta, the higher should the return be. If not, using beta as a risk measure may be an incomplete evaluation of the risk[3]. Malkiel further proposes that one might instead turn to value and size as risk factors.

[3] Which is why we include the information ratio (IR) as an evaluation metric in our analysis.

He claims that when regressing SB ETF's returns against the three initial Fama French factors, any excess performance, which is measured by alpha, can be estimated to be zero[4].

2.4.4. Cost

The third argument against SB is the cost. SB strategies are not as expensive as active management but not yet as cheap as passive strategies (Jacobs, 2014). SB deliverers might charge too much for their SB products. Too high a cost may be a reason to a potential underperformance of SB ETFs relative to their benchmarks. The cost is, not surprisingly then, an important aspect for investors when deciding to invest in SB in the first place (Agather, 2016).

The expense ratio[5] for our chosen SB ETFs varies from 0,04% up to 3,19%. In our data, cost is already withdrawn when retrieving the return and so accounted for.

2.6. ETF as a Smart Beta Vehicle

Our choice of ETF as the SB vehicle is due to the fact that ETFs have in general experienced a tremendous growth in number and value (Reilly, 2011). During the last decade, the number of ETFs has increased from 713 in 2006 to 4779 in 2016. Drivers of this explosion are likely the benefits that comes with ETFs compared to mutual funds. ETFs possess the advantage of being priced continuously and not only once a day. A second benefit is that ETFs come with a low fee (Reilly, 2011). It is hence possible for small-fund-investors to bet on ETFs and, in that way, benefit from fairly advanced strategies.

[4] See our analysis using the so-called FFC+V factor model.
[5] Expense ratio is given by a fund's operating expenses divided by the average dollar value of its assets under management (AUM).

2.7. Addition to Existing Research

When the US market represented well above half of all securities available in world markets, surveying this market exclusively would give a fair estimate of what the world market looks like. However, this has changed during the last 40 years. Other countries experience faster economic growth than do the US (Reilly, 2011). In 2016, 52% of the European asset owners surveyed had adopted SB, compared to 28% in North America and 38% in Asia Pacific (Agather, 2016). Thus, zooming in on a certain segment means you are ignoring valuable input of data (Reilly, 2011).

Previous studies of SB have been focusing on specific markets, the US for instance (Glushkov, 2014), (Arnott, 2005). Glushkov stresses the fact that extending the analysis to cover other markets besides US is a first next step for future research. We thus analyze the whole market of SB ETFs. Once omitted data, our analysis covers 446 SB ETFs, a generous amount in comparison to previous research, which analyzed 164 (Glushkov, 2014) and 117 SB ETFs (De Meyer, 2016). As Campbell puts it: "*A larger N reduces the noise in returns*" (Campbell, 2016).

A second add-on will be the comparison of SB ETFs returns to the returns of FFC+V factors. A third add-on will be the comparison of SB ETFs returns to hedge funds or mutual funds, that is, a comparison of SB strategies against active strategies. This is particularly interesting since this might indicate that SB is a disruptive innovation for active management.

Finally, investigating the active choice of SB as a complement to a passive portfolio made up of 60% equity and 40% treasury bonds yields a fourth addition. Improving diversification may namely alone justify investing in SB. Andrew Ang (2016) emphasizes that, only when applying SB to a portfolio you will be able to fully understand the complete context of investing.

As mentioned in the introduction, a survey reveals there is still a lot of uncertainty regarding SB products. Large question marks are performance, methodology, risk, costs, factor tilts and transparency (Amenc, 2015). Hence, we believe our paper will make a desired contribution to today's research regarding SB strategies.

3 Data & Methodology

3.1 Sample

This paper's primary objective is to evaluate SB ETFs that are known as being SB ETFs from a general viewpoint. Therefore, in order to understand the Smart Beta ETF market, we turn to ETF.com[6] to get information about which ETFs are generally considered as being SB. The original sample consists of 795 SB ETFs and is supposed to represent the whole global market of SB ETFs. In addition to their full name and ticker, we also retrieve information about their asset class, strategy, geography, current value of assets under management (AUM), segment and each segments' benchmark from ETF.com. Our dataset includes those SB ETFs that are not active as of the day we retrieve the data (2017-03-20) and is hence survivorship-bias free.

Data on returns of these SB ETFs is retrieved from CRSP via WRDS in the form of daily Holding Period Return (HPR), which is a return where dividends are adjusted for and numbers are in percent. We use the natural logarithm of the returns and accumulate weekly (5 trading days). This choice has its reasons in that the exchanges opening hours might differ which could give misleading results in multivariate analyses. The returns in our analyses can be defined as:

[6] a subsidiary of Chicago Board Options Exchange (CBOE)

$$r_t = \sum_{k=t-4}^{t} \log(1 + HPR_k)$$

This procedure, the source of data and accumulating the logarithmic returns, is also done for all other retrieved data on returns if not stated otherwise.

3.1.1. Supplementary Regression Input

Due to the large amount of data, using each and every self-declared benchmark[7] would be going one step too far, considering the scope of this thesis. Instead, so-called segment benchmarks are used. As it turns out, each ETF is marked as belonging to a certain segment on ETF.com. Each segment is then assigned a benchmark. We chose to set each segment's benchmark as the benchmark for every SB ETF in that segment, in order to perform the analysis. Data on these segment benchmarks is retrieved from Thomson Reuters/Datastream in the form of a Total Return Index (TRI) assuming all dividends are reinvested and with numbers in absolute terms. Here as well we use the natural logarithm of the returns and accumulate weekly:

$$r_t = \sum_{k=t-4}^{t} \log\left(\frac{TRI_k}{TRI_{k-1}}\right).$$

3.1.2. Omitted Data in General

The following applies to all analyses, if not stated otherwise:

[7] Each SB ETFs self-declared benchmark, as stated by their Factsheet or Morningstar, is applied in the research by Glushkov (2014).

We had to drop data on ETFs with missing values, missing information, those with tickers that had changed while downloading data and those with missing benchmark data.

We narrow in on equity as asset class, since this is the most common asset class among Smart Beta ETFs. We do include another asset class in one test which we will mention later. When applicable in the analysis, we divide the SB ETFs according to their strategy as identified by ETF.com, in order to detect differences between diverse factor categories. After omitting any SB ETFs that do not state equity as their asset class, we land on 14 factors. When we analyze how many SB ETFs there are in each factors' category, only 7 factor categories have a great number of SB ETFs participating from the year 2000[8]. These are Dividends, Equal, Fundamental, Growth, Momentum, Multi-factor and Value. These categories will provide the best time-series data and are so the only ones we retain. We also add the category Low Volatility to the list, since this is one of the most popular SB factors to invest in (Agather, 2016). Low Volatility has also increased very fast lately, in terms of number of ETFs as well as percentage of total AUM in the SB ETF market.

For each analysis we drop those with insufficient time-series data, that is, those with data for less than a year, or 252 trading days. In our crisis analysis, those are the ones with less than 200 days.

We use global data for the whole SB ETF market in all analyses, except for the FFC+V analysis, where only US data is used. This is due to the FFC factors data being only US data. This also applies to the mutual fund analysis.

Even though the original sample so consists of 795 SB ETFs, the actual analyses are made with a sample of 160-479 SB ETFs, depending on what specific test we perform.

[8] See Table 2, a yearly track of the number of ETFS in each category and each year.

3.2 Methodology

Following steps are taken:

1. We start out by obtaining descriptive statistics in terms of AUM, number of ETFs per year, average returns for each category and each year as well as a correlation analysis, to discover the relationships between SB factors.

2. We continue by discovering whether SB ETFs generate abnormal returns on a risk-adjusted basis when compared to their benchmark. This analysis is carried out in two different ways.

a. The first part is a regression of the mean returns per week of each SB ETF category against the weekly mean returns of each category's corresponding benchmarks. For this variant, no restriction on the length of time-series is needed and so we do not omit any data. This makes our results less survivorship-biased since closed ETFs might have less data in total and thus be omitted otherwise. The procedure is as follows:

   I. Calculating the mean of the weekly returns in the different Smart Beta ETF strategy groups.

$$r_{strat_j} = \frac{1}{N_{strat\,j}} \sum_{i \in strat_j} r_{ETF_i}$$

   II. Then we calculate the mean of the weekly returns in the corresponding Benchmark groups

$$r_{BMgroup_j} = \frac{1}{N_{strat\,j}} \sum_{i \in strat_j} r_{BM_i}$$

III. After that we conduct a robust regression of the strategy groups against the benchmark groups.

$$r_{strat_i} = \alpha_i + \beta_{BMgroup_i} * r_{BMgroup_i} + \varepsilon_i$$

IV. We also compute the yearly Sharpe Ratio, this is to see if the return above the risk free rate, adjusted for risk, is high or not.

$$Sharpe_i = \frac{E[r_{strat_i}] - r_{Rf_i}}{\sigma_{ETF_i}} * \sqrt{\frac{252}{5}}$$

V. We also compute the yearly Information Ratio, which shows the return above the benchmarks return, adjusted for risk so that it is possible to compare different information ratios.

$$IR = \frac{E[r_{strat_i} - r_{BM_i}]}{\sigma_{r_{strat_i} - r_{BM_i}}} * \sqrt{\frac{252}{5}}$$

b. In the second procedure, a regression of each SB ETF to its corresponding benchmark is performed as a first step. A mean for each factor category is calculated afterwards as a second step. We retain only those SB ETFs with time-series data for more than one year (252 trading days). The following procedure is used:

I. We perform a robust regression of each individual Smart Beta ETF against their corresponding benchmark.

$$r_{ETF_i} = \alpha_i + \beta_{BM_i} * r_{BM_i} + \varepsilon_i$$

II. We also compute yearly Sharpe Ratios and Information Ratios (see formulas above).

III. After that we compute the means of the alphas and the betas and compute beta diffs and alpha diffs, the number you should add and withdraw in order to get a 95% confidence interval.

$$\mu_{\beta_{strat_j}} = \frac{1}{N_{strat_j}} \sum_{i \in strat_j} \beta_{BM_i}$$

$$\sigma_{\beta_{strat_j}} = \sqrt{\frac{1}{N_{strat_j}} \sum_{i \in strat_j} \left(\beta_{BM_i} - \mu_{\beta_{strat_j}}\right)^2}$$

$$\beta_{DIFF} = 1.96 * \sigma_{\beta_{strat_j}}$$

3. We also analyze if SB ETFs have a positive alpha when regressed against the Fama French 3-factor model, the Carhart factor and a Volatility factor (see table below). The Fama French 3-factor model includes a market factor which is a proxy for the excess market return, where the risk-free rate is the one-month bill rate (Fama and French, 1993). The size factor, also known as Small Minus Big (SMB), is the difference between returns on small-cap portfolios and returns on big-cap portfolios. The portfolios have about the same weighted-average book-to-market equity (BE/ME). This way, BE/ME does not have an influence on their returns. The value factor, also known as High Minus Low (HML), is the difference between returns on high-BE/ME portfolios and returns on low-BE/ME portfolios. Here, portfolios have about the same weighted-

average size. This way, size does not have an influence on their returns. Carhart (1997) added a fourth factor to the 3-factor model, namely Momentum. It is built of a portfolio that is short previous 12-month loser stocks and long previous 12-month return winners. We make a second addition in terms of a volatility factor, the CBOE Volatility Index. This FFC+V analysis is applied on the US market of SB ETFs exclusively, since the FFC+V factors are based on US data. We also seek the drivers behind a potential outperformance and hence evaluate how much of the returns that can be explained by the FFC+V factors. The risk free rate is accounted for by withdrawing it from the SB ETF returns and from the return on the market.

VIX	CBOE Volatility Index	
Ex Mkt	Excess Return on market, riskfree rate is one month Treasury bill	$r_{ExMkt} = r_{Mkt} - r_{R_f}$
HML	Value, High Minus Low: Difference between returns on high- BE/ME portfolios and returns on low-BE/ME portfolios. NYSE, AMEX and NASDAQ stocks.	$HML = \frac{1}{3}(small\ value + small\ neutral + small\ growth) - \frac{1}{3}(big\ value + big\ neutral + big\ growth)$
SMB	Size, Small Minus Big: Difference between returns on small-cap portfolios and returns on big-cap portfolios. NYSE, AMEX and NASDAQ stocks.	$SMB = \frac{1}{3}(small\ value + small\ neutral + small\ growth) - \frac{1}{3}(big\ value + big\ neutral + big\ growth)$
Mom	A portfolio that is short previous 12-month loser stocks and long previous 12-month return winners.	$Mom = r_{winners} - (-r_{losers})$
R_F	One month treasury bill rate.	

This analysis is carried out in the same two ways as recently mentioned:

a. The first part is a regression based upon a beforehand computed mean of daily ETF returns of each category. The mean returns of each SB ETF category is regressed against the FFC+V factors. For this variant, no restriction on the length of time-series of individual SB ETFs is needed and so we do not omit any data. This has its reason in that we calculate a mean return of each day. This makes our results less survivorship-biased. The following procedure is used:

I. Computing daily mean of SB ETF strategies

$$r_{strat_j} = \frac{1}{N_{strat\,j}} \sum_{i \in strat_j} r_{ETF_i}$$

II. Conducting a robust regression

$$r_{strat_i} - r_{R\,f} = \alpha_i + \sum\nolimits_{j=1}^{N_{FFC+V}} \beta_{FFC+V_j} r_{FFC+V\,j} + \varepsilon_i$$

III. Computing correlation to VIX

IV. Computing Sharpe Ratio

b. In the second procedure, a regression of each SB ETF to its FFC+V factors is performed as a first step. A mean for each strategy category is calculated afterwards as a second step. We retain only those SB ETFs with time-series data for more than one year (252 trading days).

I. Conducting a robust regression

$$r_{ETF_i} - r_{Rf} = \alpha_i + \sum\nolimits_{j=1}^{N_{FFC+V}} \beta_{FFC+C_j} r_{FFC+V\,j} + \varepsilon_i$$

II. Computing mean and quantiles

$$\mu_{\beta_{f,s}} = \frac{1}{N_s} \sum_{i \in s} \beta_{f,i}$$

III. Computing diff

$$\sigma_{\beta_{f,s}} = \sqrt{\frac{1}{N_s}\sum_{i\in s}\left(\beta_{f,i} - \mu_{\beta_{f,i}}\right)^2}$$

$$\beta_{DIFF} = 1.96 * \sigma_{\beta_{strat_j}}$$

IV. Computing correlation to VIX

4. Steps 2-3 are also conducted in separate analyses during periods of crisis, considered to last between 2007-11-01 and 2009-03-01. For these analyses, we drop any SB ETFs that had less than 200 days of data during this period.

5. To find out if SB indeed is a disruptive innovation for active management, we examine the performance of mutual funds and hedge funds against SB ETFs. We perform a multivariate regression of hedge funds returns against the means of the different SB strategy categories. We also carry out the same regression with mutual funds. For the analysis of hedge funds against SB ETFs, we chose to include a second asset class, “Alternatives”, titled Long/short in tables. This asset class was the only one including SB ETFs that go both long and short. Hedge funds can go both long and short while mutual funds can only go long so it is reasonable to only include “Alternatives” when regressing against hedge funds. The following procedure is used:

   I. Robust regression of fund returns against SB factors returns

$$r_{F_i} = \alpha_i + \sum_{j=1}^{N_{strat}} \beta_{strat_j} r_{strat_j} + \varepsilon_i$$

II. Computing mean of alpha and betas

$$\mu_{\beta_{strat_j}} = \frac{1}{N_F}\sum_{i=1}^{N_F} \beta_{strat}{}_j^i$$

$$\sigma_{\beta_{strat_j}} = \sqrt{\frac{1}{N_F}\sum_{i=1}^{N_F} (\beta_{strat}{}_j^i - \mu_{\beta_{strat_j}})^2}$$

$$\beta_{DIFF} = 1.96 * \sigma_{\beta_{strat_j}}$$

6. We also investigate whether SB ETFs contribute positively as a complement to a self-constructed portfolio rather than on a stand-alone basis. This portfolio is made up of 60% equity (S&P 500) and 40% bonds (10-year Treasury bonds). We compare this equity/bond portfolio to a second portfolio made of 90% of the same equity/bond portfolio and 10% SB ETFs in terms of volatility. In the latter portfolio, we check for a higher risk-adjusted return by calculating marginal Sharpe. The following procedure is used:

I. Creating Portfolio: 60% return of S&P 500, 40% return of 10-year Treasury Bond

$$r_p = 0.4 * r_B + 0.6 * r_E$$

II. Adding an SB ETF, taking risk into consideration

$$r_{ETF+p} = \frac{0.1}{\sigma_{ETF}} * r_{ETF} + \frac{0.9}{\sigma_p} * r_p$$

III. Calculating marginal Sharpe ratio

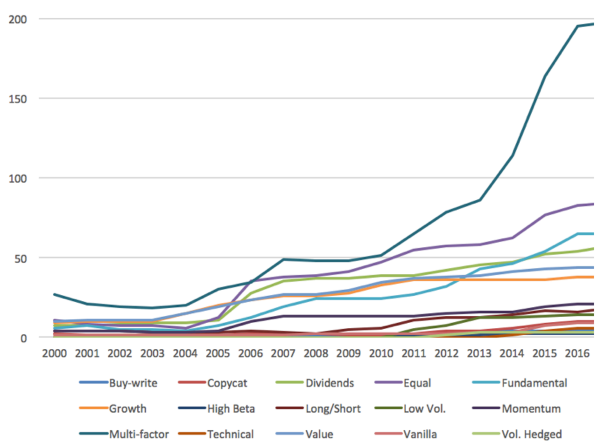
4 Results and Analysis

4.1. Descriptive statistics

Table 1a[9] provides a list of the largest SB ETFs in terms of AUM. We find that the only categories among the top 10 largest SB ETFs are Value, Growth and Dividends. This indicates that these three categories are the most popular strategies to invest in. Not surprisingly, the specific ETFs found in the top 10 globally are the exact same ones that are found when restricting the list to cover only the top 10 of the US. Hence, the largest SB ETFs can be found on the American continent.

Table 1b as well as Figure 1 below depicts how many ETFs there have been each year and within each category. The following strategies have been used in SB ETFs around the world since the year 2000: Copycat, Dividends, Equal, Fundamental, Growth, Long/Short, Momentum, Multi-factor, Value and Vanilla.

Fig.1.



[9] All tables can be found in the attached appendix in the very end of this thesis.

The same is true for the US market, with the exception of Vanilla. Out of these categories, all but Copycat, Long/Short and Vanilla have experienced quite some growth in terms of numbers of ETFs. The Multi-factor category possesses the greatest number of SB ETFs every year in the US, and almost every year globally. In 2016, it is around 100% greater in absolute numbers than the closest following category. This is to expect, since we have previously established that Multi-factor gains more and more attention[10]. However, Value tops this with the greatest AUM ratio in 2016, closely followed by the strategy Growth. Along with Dividends, these categories account for almost 70% of AUM in 2016.

Following the facts stated above, we choose to focus on Multi-factor, Momentum, Value, Dividends, Equal, Fundamental and Growth, i.e. the fastest-growing categories. We also add Low Volatility to the list, though its data starts only around 2011. This decision is grounded on the exceptional pace at which this strategy has grown ever since. The total AUM for its category accounts for nearly 5% of the AUM from all ETFs in our dataset. Buy-write, Copycat, High Beta, Technical, Vanilla and Volatility Hedged are dropped from further analyses.

4.2. Comparing Against Benchmarks

Table 5a and 5b reveals that the alphas are mostly negative and none is significantly positive. No strategy has a high Sharpe ratio. Low Volatility exhibits the highest Sharpe at 0.70 but one should bear in mind that Low Volatility has short time-series data and therefore no data during the 2007-2009 crisis. This applies to the category Low Volatility for all analyses.

Most of the categories have a beta close to one so they are very much explained by their benchmarks.

[10] See section 2.2.2.

The IR values are low or even negative. Some have a positive IR whilst a negative alpha. This can happen when both the SB ETF and the benchmark have positive returns but the ETF has higher volatility.

In short, the SB ETFs are not outperforming their benchmarks. It seems as if it would be just as good or even better to invest in the benchmark instead of in the actual Smart Beta ETF.

4.3. Returns explained by FFC+V factors

The result from the FFC+V analysis shows little difference compared to the results from the benchmark analysis (see tables 6a and 6b). Alphas are negative or close to zero and Sharpe ratios are still quite low. Low Volatility exhibits by far the highest Sharpe ratio and is the only category displaying a value above 1. Low Volatility is also the only category with a significantly positive alpha. This might, however, have its reason in the short time-series data of this category and the numbers might consequently be too good.

Value and dividend possess the highest beta to HML, which is to expect since HML is a value factor. Growth has a negative beta towards HML.

A note worth mentioning is the very low beta of Momentum, as a category, to Momentum, as a factor. The value of 0.1301 seems fairly low, considering that this particular category is supposed to be exposed to momentum. A further scrutiny regarding the categories actual tilt towards intended SB factors could hence be appropriate, however, this is out of the scope of this thesis. One might wonder, though, if this can have something to do with our sample of ETFs going long only, while the FFC+V factors actually going both long and short.

Momentum shows the highest beta to SMB followed by Equal. SMB is a size factor, so it is only natural that Momentum has a high beta to it since Momentum as a strategy is essentially about betting on high growth companies, which often happen to be small companies.

Almost all of the categories delivers negative betas to VIX that are close to zero, that is, they are not explained much by VIX. They are negative which means that the strategies probably perform badly in bad times, and this applies to Volatility as well. This is more visible when looking at the correlation to VIX. When doing this one can also notice that betas to VIX are higher, or less negative, than the correlation to VIX across categories. A high negative correlation whilst a low beta of almost zero to VIX might be because correlation does not depend on variance, while beta does. VIX probably exhibits a higher variance than the mean returns on ETFs do.

In short, SB ETFs do not outperform the Fama French Carhart factors.

4.4. Analysis of Bad Times

Analyses described above are also carried out during a period of crisis (see tables 7a-7d). This is done because we wish to examine SB strategies in comparison to active strategies, such as hedge funds that are supposed to perform better in bad times.

The benchmark regression during a period of crisis show that SB ETFs perform poorly in bad times. Growth seems to perform relatively well, but still not good. It would hence not be beneficial to invest in Smart Beta ETFs during a period of crisis instead of in an active fund that performs well in bad times.

What's interesting in the FFC+V analysis during a period of crisis, is the correlation to VIX. If there is a negative correlation to VIX in bad times, then this strategy performs poorly in bad times and an investor should invest in a fund that performs well in bad times instead, for example a hedge fund, if the investor is interested in a fund that performs well in bad times. As we can see, all categories have negative betas to VIX.

To sum up, you should rather invest in an active fund that performs well in bad times than in an SB ETF.

4.5. Active management

When looking at the results of the regressions (see tables 8a and 8b), one should interpret the numbers like this: If alpha is negative, it means that the mutual fund or hedge fund is performing worse than the SB ETF categories together, and a portfolio of SB ETFs could produce a higher return.

The results from our mutual fund regression shows that 58,72% of the alphas are negative, 13.37% of the alphas are significantly negative at the 5 % level. Consequently, it might be possible to combine SB strategies and gain a higher return at a lower cost than if investing in a mutual fund. This result is very interesting. It could mean that many mutual funds essentially are a combination of SB strategies.

The results from the hedge fund regression show that only 7 hedge funds, that is 10% of the hedge funds, produce negative alphas. These are not even negative at a significance level of 5%, which means that the hedge funds are performing better than the SB categories combined. The conclusion to be drawn is that it is not possible to combine ETF categories and replicate hedge funds.

4.6. SB ETFs as complement

When adding a SB ETF to our portfolio, 95 out of 249 SB ETFs turn out to contribute positively to the Sharpe ratio (see table 9). In other words, 38,15% of the SB ETFs added value to our equity/bond portfolio. Furthermore, all categories have a positive marginal Sharpe in the 90th quantile. This means that at least some SB ETFs in each category contribute positively to the return when added to the portfolio.

5 Implications and Conclusion

We find that each SB strategy delivers very low positive or even negative alphas, when regressed against their benchmark. None of the categories except for Low Volatility produce an alpha above zero with a significance level of 95%. And caution should be taken when interpreting the results for this category due to short time-series data. The Sharpe ratios are mostly positive but very small, and the information ratios are either negative or not far above zero. All in all, the SB strategies do not outperform their benchmarks.

When regressing against FFC+V factors, the results are similar with alphas that are low or negative. SB categories do not outperform the FFC+V factors. Furthermore, when analyzing during times of crisis we see that SB strategies perform poorly, and this is also seen in the negative correlation to VIX. Our conclusion is that SB ETFs are not outperforming when evaluated on a stand-alone basis.

However, as a complement to a passive equity/bond portfolio, SB ETFs can add value. Additionally, if combining several different SB ETF strategies, it might be possible to replicate a mutual fund's performance. A substantial number of mutual funds analyzed do not outperform our SB strategies together. This means that it can be possible to combine SB ETF strategies and produce a higher alpha than a mutual fund. We cannot draw the same conclusion when it comes to hedge funds.

In short, Smart Beta might be more than just smart marketing for an informed investor. If choosing the right SB ETF, the fund can add value as a complement to a passive equity/bond portfolio. Or, if combining SB ETFs from different SB categories you might be able to form a portfolio that performs better than a mutual fund. This is, however, difficult for the average investor to do.

5.2 Limitations of our study

Due to downloading restrictions, we only had the possibility to retrieve data from the year 2010 to form our sample of hedge funds. There was also a constraint as to how many funds' returns we could download. The maximum limit was returns of 100 randomly selected hedge funds.

Furthermore, we have a limited amount of SB ETFs that go both long and short. Therefore, the results from our hedge fund analysis might be tilted in favor of hedge funds.

We have narrowed in on equity as asset class, which also might give misleading results especially for the analyses regarding active strategies.

Lastly, the decision to use segment benchmarks might also be a limitation of our study. Segment benchmarks may not be the perfect benchmark for each specific SB ETF to be judged against.

5.3 Further Research

Due to our limited sample of hedge funds, it would be appropriate to redo the hedge fund analysis with an extended supply of hedge funds for longer time-series. It would also be fruitful to expand the number of ETFs that go both long and short in that analysis as well, since we had only a few of those.

How one can replicate a mutual funds returns through combining SB ETFs is another possible topic for further research. One could also investigate Multi-factor models more, to see what diversification benefits there could be. A look into intended factor exposure could be a last suggestion for further investigation.

6 References

Agather, R. & Gunthorp, P. 2016, *, Smart beta : 2016 global survey findings from asset owners* [Homepage of FTSE Russell], [Online]. Available: http://www.ftserussell.com/index-series/index-spotlights/smart-beta-factor-indexes/get-deeper-understanding-smart-beta [2016, 05/09].

Amenc, N., Goltz, F., Le Sourd, V. & Lodh, A. 2015, *Alternative Equity Beta Investing: A Survey*, EDHEC-Risk Institute.

Amenc, N., Goltz, F., Lodh, A. & Martellini, L. 2014, "Towards smart equity factor indices: Harvesting risk premia without taking unrewarded risks", *Journal of Portfolio Management,* vol. 40, no. 4, pp. 106-122.

Ang, A. 2016, *, Smart Beta Guide* [Homepage of Blackrock], [Online]. Available: https://www.blackrock.com/ca/intermediaries/en/literature/brochure/smart-beta-guide-en-ca.pdf [2017, 05/09].

Arnott, R.D. 2014, *, What "Smart Beta" Means to Us*. Available: https://www.researchaffiliates.com/en_us/publications/articles/292_what_smart_beta_means_to_us.html [2017, 05/09].

Arnott, R.D., Beck, N., Kalesnik, V. & West, J. 2016, *, How Can "Smart Beta" Go Horribly Wrong?*. Available: https://www.researchaffiliates.com/en_us/publications/articles/442_how_can_smart_beta_go_horribly_wrong.html [2017, 05/09].

Arnott, R.D., Hsu, J. & Moore, P. 2005, "Fundamental indexation", *Financial Analysts Journal,* vol. 61, no. 2, pp. 83-99.

Bender, J., Briand, R., Melas, D. & Subramanian, R.A. 2013, "Foundations of Factor Investing", .

Blitz, D. & Swinkels, L. 2008, "Fundamental Indexation: An Active Value Strategy in Disguise", *Journal of Asset Management,* vol. 9, no. 4, pp. 264-269.

Carhart, M.M. 1997, "On persistence in mutual fund performance", *Journal of Finance,* vol. 52, no. 1, pp. 57-82.

Chow, T.-., Hsu, J., Kalesnik, V. & Little, B. 2011, "A survey of alternative equity index strategies", *Financial Analysts Journal,* vol. 67, no. 5, pp. 37-57.

Cochrane, J.H. 2011, "Presidential Address: Discount Rates", *Journal of Finance,* vol. 66, no. 4, pp. 1047-1108.

De Meyer, D. & Rodts, T. 2016, *Can European investors outsmart the market? - A study on the performance of European Smart Beta ETFs*.

Evans, J. Feb 1, 2015, *, Smart Beta is no guarantee you will beat the market*. Available: https://www.ft.com/content/2d00969c-a32f-11e4-9c06-00144feab7de#comments [2017, 05/09].

Fama, E.F. & French, K.R. 1998, "Value versus Growth: The International Evidence", *Journal of Finance,* vol. 53, no. 6, pp. 1975-1999.

Fama, E.F. & French, K.R. 1993, "Common Risk Factors in the Returns on Stock and Bonds", *Journal of Financial Economics,* vol. 33, no. 1, pp. 3-56.

Glushkov, D. 2014, *, How smart are "Smart Beta ETFs"?*. Available: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2594941 [2017, 02/26].

Harvey, C.R., Liu, Y. & Zhu, H. 2016, ". . . And the Cross-Section of Expected Returns", *Review of Financial Studies,* vol. 29, no. 1, pp. 5-68.

Haugen, R.A. & Baker, N.L. 1991, "The Efficient Market Inefficiency of Capitalization-Weighted Stock Portfolios", *Journal of Portfolio Management,* vol. 17, no. 3, pp. 35-40.

Hsu, J. & Kalesnik, V. 2014, "Finding Smart beta in the Factor Zoo", .

Hsu, J. 2006, "Cap Weighted Portfolios Are Sub-optimal Portfolios", *Journal of Investment Management,* vol. 4, no. 3, pp. 44-53.

Jacobs, B.I. 2015, "Is smart beta state of the art?", *Journal of Portfolio Management,* vol. 41, no. 4, pp. 1-3.

Jacobs, B.I. & Levy, K.N. 2014, "Smart beta versus smart alpha", *Journal of Portfolio Management,* vol. 40, no. 4, pp. 4-7.

Jacobs, B.I. & Levy, K.N. 2015, "Smart Beta: Too Good to Be True?", *Journal of Financial Perspectives,* vol. 3, no. 2, pp. 155-159.

Jegadeesh, N. & Titman, S. 2001, "Profitability of momentum strategies: An evaluation of alternative explanations", *Journal of Finance,* vol. 56, no. 2, pp. 699-720.

Jegadeesh, N. & Titman, S. 1993, "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency", *Journal of Finance,* vol. 48, no. 1, pp. 65-91.

Kahn, R.N. & Lemmon, M. 2015, "Smart beta: The owner's manual", *Journal of Portfolio Management,* vol. 41, no. 2, pp. 76-83.

Kahn, R.N. & Lemmon, M. 2016, "The Asset Manager's Dilemma: How Smart Beta Is Disrupting the Investment Management Industry", *Financial Analysts Journal,* vol. 72, no. 1, pp. 15-20.

Malkiel, B.G. 2014, "Is smart beta really smart?", *Journal of Portfolio Management,* vol. 40, no. 5, pp. 127-134.

Market Strategies International 2014, *The Evolution of Smart Beta ETFs*, Invesco Powershares.

Melas, D. 2016, "Power to the people: The profound impact of factor investing on long-term portfolio management", *Journal of Portfolio Management,* vol. 42, no. 2, pp. 6-8.

Reilly, F.K. & Brown, K.C. 2011, "Investment Analysis & Portfolio Management", , no. 10th edition, pp. 1080.

Stoneberg, J. & Smith, B. 2017, *Getting smart about beta - examining smart beta equity methodologies and their impact over full market cycles*, Invesco.

7 Appendix

Table 1a. Top 15 Largest Smart Beta Exchange-Traded Funds; Global (as of May 05, 2017)
Table below presents Assets Under Management (AUM) in billion as of the end of 2016, as well as the AUM ratio, for each of the 15 largest Smart Beta ETFs as well as the full name of each fund, its ticker, strategy and segment.

GLOBAL

Ticker	Name	Strategy	Segment	Segemtn Benchmark	AUM $Bil.	AUM ratio
IWD	iShares Russell 1000 Value ETF	Value	Equity: U.S. - Large Cap Value	MSCI USA Large Value	37,29	6,27%
IWF	iShares Russell 1000 Growth ETF	Growth	Equity: U.S. - Large Cap Growth	MSCI USA Large Growth	35,55	5,98%
VTV	Vanguard Value Index Fund	Value	Equity: U.S. - Large Cap Value	MSCI USA Large Value	30,44	5,12%
VUG	Vanguard Growth Index Fund	Growth	Equity: U.S. - Large Cap Growth	MSCI USA Large Growth	26,59	4,47%
VIG	Vanguard Dividend Appreciation Index Fund	Dividends	Equity: U.S. - Total Market	MSCI USA Investable Markets	23,91	4,02%
VYM	Vanguard High Dividend Yield Index Fund	Dividends	Equity: U.S. - High Dividend Yield	MSCI USA IMI High Yield Dividend	17,77	2,99%
IVW	iShares S&P 500 Growth ETF	Growth	Equity: U.S. - Large Cap Growth	MSCI USA Large Growth	17,59	2,96%
DVY	iShares Select Dividend ETF	Dividends	Equity: U.S. - High Dividend Yield	MSCI USA IMI High Yield Dividend	17,15	2,88%
SDY	SPDR S&P Dividend ETF	Dividends	Equity: U.S. - High Dividend Yield	MSCI USA IMI High Yield Dividend	15,46	2,60%
IVE	iShares S&P 500 Value ETF	Value	Equity: U.S. - Large Cap Value	MSCI USA Large Value	13,59	2,28%
RSP	Guggenheim S&P 500 Equal Weight ETF	Equal	Equity: U.S. - Large Cap	MSCI USA Large Cap	13,33	2,24%
USMV	iShares Edge MSCI Min Vol USA ETF	Low Volatility	Equity: U.S. - Total Market	MSCI USA Investable Markets	12,72	2,14%
VBR	Vanguard Small Cap Value Index Fund	Value	Equity: U.S. - Small Cap Value	MSCI USA Small Cap Value	11,25	1,89%
IWS	iShares Russell Mid-Cap Value ETF	Value	Equity: U.S. - Mid Cap Value	MSCI USA Mid Cap	9,43	1,59%
IWN	iShares Russell 2000 Value ETF	Value	Equity: U.S. - Small Cap Value	MSCI USA Small Cap Value	8,65	1,45%
Total					**290,72**	**48,87%**
Tot top *5*					**153,78**	**25,85%**

Table 1b. Top 15 Largest Smart Beta Exchange-Traded Funds; US (as of May 05, 2017)
Table below presents Assets Under Management (AUM) in billion as of the end of 2016, as well as the AUM ratio, for each of the 15 largest Smart Beta ETFs as well as the full name of each fund, its ticker, strategy and segment.

US

Ticker	Name	Strategy	Segment	Segment Benchmark	AUM $Bil.	AUM ratio
IWD	iShares Russell 1000 Value ETF	Value	Equity: U.S. - Large Cap Value	MSCI USA Large Value	37,29	7,17%
IWF	iShares Russell 1000 Growth ETF	Growth	Equity: U.S. - Large Cap Growth	MSCI USA Large Growth	35,55	6,83%
VTV	Vanguard Value Index Fund	Value	Equity: U.S. - Large Cap Value	MSCI USA Large Value	30,44	5,85%
VUG	Vanguard Growth Index Fund	Growth	Equity: U.S. - Large Cap Growth	MSCI USA Large Growth	26,59	5,11%
VIG	Vanguard Dividend Appreciation Index Fund	Dividends	Equity: U.S. - Total Market	MSCI USA Investable Markets	23,91	4,60%
VYM	Vanguard High Dividend Yield Index Fund	Dividends	Equity: U.S. - High Dividend Yield	MSCI USA IMI High Yield Dividend	17,77	3,42%
IVW	iShares S&P 500 Growth ETF	Growth	Equity: U.S. - Large Cap Growth	MSCI USA Large Growth	17,59	3,38%
DVY	iShares Select Dividend ETF	Dividends	Equity: U.S. - High Dividend Yield	MSCI USA IMI High Yield Dividend	17,15	3,30%
SDY	SPDR S&P Dividend ETF	Dividends	Equity: U.S. - High Dividend Yield	MSCI USA IMI High Yield Dividend	15,46	2,97%
IVE	iShares S&P 500 Value ETF	Value	Equity: U.S. - Large Cap Value	MSCI USA Large Value	13,59	2,61%
RSP	Guggenheim S&P 500 Equal Weight ETF	Equal	Equity: U.S. - Large Cap	MSCI USA Large Cap	13,33	2,56%
USMV	iShares Edge MSCI Min Vol USA ETF	Low Volatility	Equity: U.S. - Total Market	MSCI USA Investable Markets	12,72	2,45%
VBR	Vanguard Small Cap Value Index Fund	Value	Equity: U.S. - Small Cap Value	MSCI USA Small Cap Value	11,25	2,16%
IWS	iShares Russell Mid-Cap Value ETF	Value	Equity: U.S. - Mid Cap Value	MSCI USA Mid Cap	9,43	1,81%
IWN	iShares Russell 2000 Value ETF	Value	Equity: U.S. - Small Cap Value	MSCI USA Small Cap Value	8,65	1,66%
Total					**290,72**	**55,89%**
Tot top *5*					**153,78**	**29,56%**

Table 2a. Yearly Track of No. of SB ETFs by category; Global (as of May 05, 2017) The tables below reveal the number of SB ETFs that existed within a particular category each year. The first table shows the number for the whole market and the second one for the US market. The bottom line provides the latest details (2016) on the AUM ratio for each category.

GLOBAL

Strategy	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	# ETFs	AUM ratio 2016
Buy-write	0	0	0	0	0	0	0	1	1	1	1	1	1	4	4	4	4	4	-
Copycat	2	1	1	1	1	1	2	2	2	1	1	2	4	4	6	8	10	10	-
Dividends	7	7	8	9	9	11	28	35	37	37	39	39	42	45	47	52	54	57	18,92%
Equal	11	8	7	7	6	12	35	38	39	41	47	55	57	58	62	77	83	84	6,99%
Fundamental	6	7	5	5	4	7	12	19	24	24	24	27	32	43	46	54	65	65	8,36%
Growth	9	10	10	10	15	20	23	26	26	28	33	36	36	36	36	36	38	38	23,63%
High Beta	0	0	0	0	0	0	0	0	0	0	0	1	1	1	2	2	2	2	0,07%
Long/Short	4	4	4	3	3	3	4	3	2	5	6	11	12	12	14	17	16	18	0,26%
Low Vol.	0	0	0	0	0	0	0	0	0	0	0	5	7	12	12	13	14	14	6,06%
Momentum	4	4	4	3	3	4	10	13	13	13	13	13	15	16	16	19	21	21	0,98%
Multi-factor	27	21	19	18	20	30	34	49	48	48	51	65	78	86	114	164	195	198	8,84%
Technical	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	4	6	6	0,06%
Value	10	11	11	11	15	19	23	27	27	29	34	37	38	39	41	43	44	44	25,83%
Vanilla	1	1	1	1	1	1	1	1	2	2	2	2	2	3	3	7	9	9	-
Vol. Hedged	0	0	0	0	0	0	0	0	0	0	0	0	1	3	3	3	3	3	0,01%
Total	**81**	**74**	**70**	**68**	**77**	**108**	**172**	**214**	**221**	**229**	**251**	**294**	**326**	**362**	**407**	**503**	**564**	**573**	**100%**

Table 2b. Yearly Track of No. of SB ETFs by category; US (as of May 05, 2017)

US

Strategy	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	# ETFs	AUM ratio 2016
Buy-write	0	0	0	0	0	0	0	1	1	1	1	1	1	4	4	4	4	4	-
Copycat	2	1	1	1	1	1	2	2	2	1	1	2	4	4	5	6	8	8	-
Dividends	5	5	5	6	7	8	14	14	14	14	14	14	15	16	16	19	17	19	18,29%
Equal	5	4	3	4	4	10	31	32	30	31	35	41	41	42	45	57	60	60	7,45%
Fundamental	5	5	3	3	2	5	10	12	16	16	16	18	20	28	30	34	40	40	7,50%
Growth	9	10	10	10	15	19	22	25	25	27	32	35	35	35	35	35	37	37	26,50%
High Beta	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0,05%
Long/Short	1	1	1	1	1	1	1	0	0	0	1	5	5	5	5	6	6	6	0,01%
Low Vol.	0	0	0	0	0	0	0	0	0	0	0	2	2	7	7	7	8	8	4,20%
Momentum	4	4	4	3	3	4	10	11	11	11	11	11	13	14	14	16	16	16	0,99%
Multi-factor	16	14	13	13	16	26	29	42	40	40	42	46	50	51	59	83	103	105	6,42%
Technical	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	4	4	0,03%
Value	10	11	11	11	15	18	22	26	26	28	33	36	37	38	39	40	41	41	28,55%
Vanilla	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	-
Vol. Hedged	0	0	0	0	0	0	0	0	0	0	0	0	1	3	3	3	3	3	0,01%
Total	**57**	**55**	**51**	**52**	**64**	**92**	**141**	**165**	**166**	**170**	**187**	**213**	**226**	**249**	**265**	**314**	**349**	**353**	**100%**

Table 3a. Correlation Between Smart Beta Factors; Global

GLOBAL

Strategy	Dividends	Equal	Fundamental	Growth	Long/Short	Low Vol.	Momentum	Multi-factor	Value
Dividends	1,0000								
Equal	0,5441	1,0000							
Fundamental	0,5609	0,6522	1,0000						
Growth	0,5193	0,7260	0,6580	1,0000					
Long/Short	0,2815	0,3537	0,3531	0,3388	1,0000				
Low Vol.	0,9357	0,8961	0,9355	0,8949	0,4874	1,0000			
Momentum	0,4650	0,5608	0,5982	0,5648	0,2770	0,9049	1,0000		
Multi-factor	0,5946	0,6846	0,7074	0,7228	0,3568	0,9271	0,6118	1,0000	
Value	0,6203	0,7818	0,7622	0,7522	0,3918	0,9141	0,6672	0,7469	1,0000

Table 3b. Correlation Between Smart Beta Factors; US.

				US					
Strategy	**Dividends**	**Equal**	**Fundamental**	**Growth**	**Long/Short**	**Low Vol.**	**Momentum**	**Multi-factor**	**Value**
Dividends	1,0000								
Equal	0,6308	1,0000							
Fundamental	0,6074	0,5472	1,0000						
Growth	0,6423	0,7137	0,5674	1,0000					
Long/Short	0,0911	0,0892	0,0545	0,0559	1,0000				
Low Vol.	0,9507	0,8811	0,9103	0,8986	-0,0436	1,0000			
Momentum	0,6026	0,5335	0,5319	0,5632	0,0525	0,8954	1,0000		
Multi-factor	0,6571	0,6117	0,5781	0,6809	0,0854	0,9033	0,5652	1,0000	
Value	0,7931	0,7557	0,6658	0,7510	0,1190	0,9080	0,6640	0,6986	1,0000

Table 4a. Mean Returns For Each Year And For Each Category; Global. Tables below present average annual return for each category and for each consecutive year. Numbers are shown in percent.

GLOBAL

Strategy	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Dividends	-0,0327	0,0855	-0,0079	0,0476	0,0052	0,0420	0,0885	0,0008	-0,2764	0,2020	0,0897	-0,0311	0,1015	0,1497	0,0161	-0,0654	0,1257
Equal	-0,0038	0,0091	-0,0176	0,0242	0,0128	0,0195	0,0142	0,0298	-0,1725	0,1827	0,0954	-0,0536	0,0964	0,2270	0,0421	-0,0517	0,1188
Fundamental	-0,0179	0,0266	0,0099	0,0238	0,0200	0,0221	0,0258	0,0011	-0,1295	0,1501	0,0688	-0,0215	0,0745	0,1466	0,0341	-0,0444	0,1341
Growth	-0,0228	-0,0259	-0,0598	0,0872	0,0377	0,0405	0,0577	0,0670	-0,2707	0,2617	0,1970	-0,0036	0,1425	0,3380	0,0851	0,0234	0,0933
Long/Short	-0,0135	0,0224	-0,0082	0,0479	0,0526	0,0528	0,0399	0,0177	-0,0242	0,0209	0,0057	-0,0067	0,0131	0,0159	0,0058	-0,0294	0,0301
Low Vol.	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0110	0,0708	0,1368	0,0854	-0,0096	0,1100
Momentum	-0,0093	0,1276	0,0402	0,1690	0,0087	0,0210	0,0594	0,0519	-0,2360	0,1703	0,1392	-0,0197	0,1031	0,2565	0,0426	-0,0074	0,0468
Multi-factor	-0,0069	-0,0083	0,0065	0,0438	0,0044	0,0272	0,0082	-0,0053	-0,0976	0,0892	0,0490	-0,0246	0,0434	0,0971	0,0138	-0,0440	0,0922
Value	0,0281	0,0004	0,0097	0,1084	0,0540	0,0308	0,1022	-0,0226	-0,2216	0,1924	0,1426	-0,0133	0,1469	0,3114	0,0850	-0,0600	0,2165

Table 4b. Mean Returns For Each Year And For Each Category; US. Tables below present average annual return for each category and for each consecutive year. Numbers are shown in percent.

US

Strategy	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Dividends	-0,0512	0,0713	0,0545	0,1148	0,0199	0,0070	0,1423	-0,0326	-0,2669	0,1191	0,1251	0,0573	0,0940	0,2314	0,1147	-0,0201	0,1766
Equal	0,0011	0,0251	-0,0045	0,0343	0,0153	0,0327	0,0182	0,0201	-0,1896	0,1959	0,1227	-0,0218	0,1268	0,2706	0,0776	-0,0422	0,1111
Fundamental	-0,0391	0,0261	0,0144	0,0342	0,0286	0,0175	0,0227	0,0047	-0,1318	0,1468	0,0829	0,0017	0,0727	0,2102	0,0699	-0,0382	0,1622
Growth	-0,0234	-0,0266	-0,0614	0,0896	0,0387	0,0386	0,0534	0,0648	-0,2672	0,2623	0,1988	-0,0002	0,1414	0,3413	0,0890	0,0230	0,0967
Long/Short	-0,0071	0,0724	0,0218	0,0440	0,0293	0,0212	0,0379	0,0000	0,0000	0,0000	0,0035	-0,0123	-0,0061	0,0298	-0,0123	-0,0275	0,0289
Low Vol.	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0158	0,0261	0,1830	0,1364	0,0229	0,1646
Momentum	-0,0122	0,1674	0,0528	0,2218	0,0114	0,0275	0,0780	0,0675	-0,2420	0,1638	0,1538	-0,0062	0,1133	0,3151	0,0627	-0,0008	0,0607
Multi-factor	-0,0230	-0,0184	0,0068	0,0305	-0,0007	0,0472	0,0188	-0,0049	-0,1509	0,1053	0,0897	-0,0119	0,0547	0,1562	0,0464	-0,0313	0,1159
Value	0,0302	0,0004	0,0104	0,1164	0,0579	0,0304	0,1023	-0,0253	-0,2277	0,1995	0,1519	-0,0112	0,1531	0,3288	0,0975	-0,0585	0,2262

Table 5a. Benchmark regression – First variant. Regression of SB ETF categories against corresponding benchmark groups. Mean of each SB ETF category is calculated first and then regressed to corresponding means of benchmarks. Table show, for each category, the Sharpe ratio, IR, alpha and betas. All columns titled Diff 95 represent the amount to be added or withdrawn from the value to the left, in order to get a 95% confidence interval.

GLOBAL

Strategy	# ETFs	Sharpe	IR	Alpha	Alpha diff 95	Beta	Beta diff 95
Dividends	51	0,1871	-0,0649	-0,0007	0,0007	0,9808	0,0315
Equal	66	-0,3033	-0,7742	-0,0011	0,0005	1,1813	0,0195
Fundamental	62	0,2668	0,1551	-0,0006	0,0006	1,0848	0,0261
Growth	38	0,1171	0,1019	-0,0002	0,0002	0,9886	0,0068
Low Vol.	14	0,6954	0,0556	0,0002	0,0007	0,7735	0,0315
Momentum	21	0,4152	0,3271	-0,0003	0,0006	1,0484	0,0241
Multi-factor	183	-0,1434	-0,6152	-0,0013	0,0006	1,0260	0,0259
Value	44	0,3507	0,2790	-0,0003	0,0003	1,0622	0,0119
Total	**479**						

Table 5b. Benchmark regression – Second variant. Regression of each SB ETF against corresponding benchmark. Mean of each SB ETF category is calculated after conducting the regression to the mean of the corresponding group of benchmark. Table show, for each category, the Sharpe ratio, IR, alpha and betas. All columns titled Diff 95 represent the amount to be added or withdrawn from the value to the left, in order to get a 95% confidence interval.

GLOBAL

Strategy	# ETFs	Sharpe	Sharpe 10% quantile	Sharpe 90% quantile	IR	IR 10% quantile	IR 90% quantile	Alpha	Alpha diff 95	Alpha 10% quantile	Alpha 90% quantile	Beta	Beta diff 95	Beta 10% quantile	Beta 90% quantile
Dividends	44	0,1860	-0,1426	0,5034	-0,2069	-0,5578	0,2085	-0,0006	0,0002	-0,0016	0,0002	0,9996	0,0002	0,8020	1,2221
Equal	62	0,1684	-0,2650	0,5981	-0,1464	-0,6553	0,2434	-0,0009	0,0004	-0,0014	0,0005	1,0379	0,0004	0,7887	1,2970
Fundamental	53	0,3348	-0,0674	0,8120	-0,0186	-0,6157	0,4114	-0,0002	0,0003	-0,0012	0,0008	1,0168	0,0003	0,8594	1,1863
Growth	36	0,3601	0,1203	0,7871	-0,0525	-0,4120	0,3510	-0,0002	0,0001	-0,0006	0,0001	0,9898	0,0001	0,9344	1,0440
Low Vol.	13	0,7040	-0,0874	1,2273	-0,1504	-0,6344	0,4802	0,0002	0,0003	-0,0008	0,0012	0,7953	0,0003	0,6541	1,0670
Momentum	19	0,2960	-0,1137	0,7132	-0,1652	-0,5682	0,4045	0,0001	0,0003	-0,0008	0,0010	0,9835	0,0003	0,7426	1,1466
Multi-factor	152	0,1904	-0,3191	0,7396	-0,2252	-0,8437	0,3771	-0,0007	0,0002	-0,0016	0,0007	0,9205	0,0002	0,5683	1,1548
Value	43	0,3975	0,1857	0,7643	-0,0074	-0,2155	0,2410	-0,0003	0,0001	-0,0010	0,0001	1,0363	0,0001	0,9782	1,1403
Total	422														

Table 6a. Fama French Carhart Volatility regression – First variant Regression of the mean of SB ETF categories against Fama French Carhart Volatility factors. Table show, for each category, the Sharpe ratio, alpha, correlation and beta to VIX as well as betas to the FFC factors. All columns titled Diff 95 represent the amount to be added or withdrawn from the value to the left, in order to get a 95% confidence interval. VIX corr is correlation to volatility index.

US

Strategy	# ETFs	Sharpe	VIX corr.	Alpha	Alpha diff 95	VIX	VIX diff 95	Ex Mkt	Ex Mkt diff 95	HML	HML diff 95	Mom	Mom diff 95	SMB	SMB diff 95
Dividends	19	0,2084	-0,5935	0,0001	0,0006	-0,0055	0,0069	0,7557	0,0372	0,2983	0,0422	-0,0831	0,0267	0,0260	0,0438
Equal	60	0,2623	-0,6216	-0,0002	0,0005	0,0037	0,0063	1,0847	0,0336	0,1227	0,0381	-0,0124	0,0241	0,2947	0,0395
Fundamental	40	0,3165	-0,5019	-0,0001	0,0005	0,0069	0,0057	1,0011	0,0305	0,1156	0,0346	-0,0528	0,0219	0,2421	0,0359
Growth	37	0,1315	-0,6040	-0,0001	0,0003	0,0025	0,0037	1,0494	0,0200	-0,1725	0,0226	0,0281	0,0143	0,2838	0,0235
Long/Short	6	0,4403	-0,1242	0,0010	0,0011	0,0111	0,0133	0,1356	0,0737	0,1768	0,0952	-0,0204	0,0540	0,1032	0,0821
Low Vol.	8	1,1252	-0,8113	0,0008	0,0007	-0,0133	0,0084	0,6430	0,0623	0,1311	0,0871	0,1313	0,0513	-0,0350	0,0744
Momentum	16	0,4755	-0,5399	0,0001	0,0006	0,0002	0,0070	1,0034	0,0374	0,0305	0,0425	0,1301	0,0269	0,3039	0,0441
Multi-factor	105	-0,2423	-0,6034	-0,0005	0,0006	-0,0009	0,0065	0,9548	0,0349	0,0635	0,0396	0,0208	0,0251	0,2279	0,0410
Value	41	0,3934	-0,6877	0,0002	0,0003	-0,0042	0,0035	0,9225	0,0186	0,3751	0,0211	-0,0363	0,0134	0,2834	0,0219
Total	332														

Table 6b. Fama French Carhart Volatility regression – Second variant. Mean of each SB ETF category is calculated after conducting the regression of the SB ETF against Fama French Carhart Factors and Volatility. Table show, for each category, the Sharpe ratio, alpha, betas to the FFC factors as well as the correlation and beta to VIX. All columns titled Diff 95 represent the amount to be added or withdrawn from the value to the left, in order to get a 95% confidence interval. VIX corr is correlation to volatility index. 10% quantile and 90% quantile is shown to the left of the mean and diff 95.

US

Strategy	# ETFs	Sharpe	Sharpe 10% quantile	Sharpe 90% quantile	Alpha	Alpha diff 95	Alpha 10% quantile	Alpha 90% quantile	Ex Mkt	Ex Mkt diff 95	Ex Mkt 10% quantile	Ex Mkt 90% quantile	HML	HML diff 95	HML 10% quantile	HML 90% quantile
Dividends	16	0,3715	-0,0380	0,5815	0,0001	0,0003	-0,0003	0,0008	0,8196	0,0003	0,7169	0,9128	0,2174	0,0003	0,0503	0,3901
Equal	46	0,3415	-0,0160	0,7746	0,0000	0,0004	-0,0017	0,0016	1,0706	0,0004	0,7597	1,3618	-0,0002	0,0004	-0,3946	0,4898
Fundamental	33	0,4388	-0,0266	0,9325	-0,0002	0,0006	-0,0009	0,0008	0,9560	0,0006	0,6821	1,1022	0,1207	0,0006	-0,1008	0,3861
Growth	35	0,4075	0,1305	0,8641	0,0000	0,0001	-0,0004	0,0003	1,0423	0,0001	0,9752	1,1467	-0,1456	0,0001	-0,2899	0,0596
Long/Short	6	0,1577	-0,2680	0,4701	0,0003	0,0007	-0,0007	0,0010	-0,0385	0,0007	-0,5636	0,1460	0,1935	0,0007	-0,1372	0,5136
Low Volatility	7	1,1314	0,9527	1,3219	0,0008	0,0004	0,0003	0,0016	0,7424	0,0004	0,6251	0,8722	0,1757	0,0004	-0,0652	0,4821
Momentum	14	0,4112	0,1820	0,8169	0,0003	0,0003	-0,0008	0,0016	0,9825	0,0003	0,7598	1,2291	-0,0002	0,0003	-0,1608	0,1898
Multi-factor	73	0,2498	-0,5849	0,7735	-0,0010	0,0006	-0,0033	0,0010	0,8148	0,0006	0,3768	1,2265	0,1042	0,0006	-0,2085	0,3852
Value	39	0,4694	0,2483	0,8089	0,0001	0,0001	-0,0002	0,0005	0,9716	0,0001	0,9160	1,0259	0,2979	0,0001	0,1636	0,4659
Total	269															

Strategy	# ETFs	Mom	Mom diff 95	Mom 10% quantile	Mom 90% quantile	SMB	SMB diff 95	SMB 10% quantile	SMB 90% quantile	VIX	VIX diff 95	VIX 10% quantile	VIX 90% quantile	VIX corr.	VIX corr. 10% quantile	VIX corr. 90% quantile
Dividends	16	-0,0847	0,0003	-0,1434	-0,0126	0,0138	0,0003	-0,2457	0,3695	-0,0033	0,0003	-0,0117	0,0041	-0,6184	-0,7330	-0,4612
Equal	46	-0,0607	0,0004	-0,2088	0,1080	0,2799	0,0004	-0,0963	0,6415	-0,0011	0,0004	-0,0196	0,0158	-0,6226	-0,7352	-0,5228
Fundamental	33	-0,0697	0,0006	-0,2444	0,0291	0,1302	0,0006	-0,1812	0,8383	0,0024	0,0006	-0,0109	0,0187	-0,6804	-0,8904	-0,2983
Growth	35	0,0532	0,0001	-0,0009	0,1679	0,2781	0,0001	-0,1268	0,8272	0,0017	0,0001	-0,0028	0,0074	-0,7326	-0,8162	-0,6841
Long/Short	6	0,0500	0,0007	-0,2407	0,5734	0,0588	0,0007	-0,1359	0,4305	-0,0089	0,0007	-0,0403	0,0099	-0,0960	-0,6433	0,4479
Low Volatility	7	0,1289	0,0004	0,0356	0,2465	0,0695	0,0004	-0,2354	0,5546	-0,0069	0,0004	-0,0158	0,0012	-0,7870	-0,8596	-0,6942
Momentum	14	0,1164	0,0003	-0,0073	0,2770	0,2898	0,0003	-0,0967	0,5387	-0,0033	0,0003	-0,0122	0,0057	-0,6155	-0,7528	-0,3347
Multi-factor	73	-0,0325	0,0006	-0,1363	0,1406	0,2590	0,0006	-0,1209	0,6760	-0,0064	0,0006	-0,0261	0,0109	-0,5657	-0,8415	-0,1546
Value	39	-0,0834	0,0001	-0,2217	0,0010	0,2290	0,0001	-0,1986	0,8005	-0,0002	0,0001	-0,0050	0,0051	-0,7148	-0,8056	-0,6557
Total	269															

Table 7a. Evaluating SB ETFs during periods of crisis; first variant against benchmark. Regression of SB ETF categories against corresponding benchmark groups for a period of crisis defined as 2007-11-01 - 2009-03-01. Mean of each SB ETF category is calculated first and then regressed to corresponding means of benchmarks. Table show, for each category, the Sharpe ratio, IR, alpha and beta. All columns titled Diff 95 represent the amount to be added or withdrawn from the value to the left, in order to get a 95% confidence interval.

GLOBAL

Strategy	# ETFs	# ETFs bad times	Sharpe	Sharpe bad times	IR	IR bad times	Alpha	Alpha diff 95	Alpha bad times	Alpha diff 95 bad times
Dividends	51	33	0,1871	-2,0085	-0,0649	-1,5299	-0,0007	0,0007	-0,0024	0,0033
Equal	66	36	-0,3033	-1,4609	-0,7742	-0,3453	-0,0011	0,0005	0,0011	0,0016
Fundamental	62	23	0,2668	-1,6100	0,1551	-0,1615	-0,0006	0,0006	-0,0005	0,0029
Growth	38	26	0,1171	-1,5059	0,1019	0,2226	-0,0002	0,0002	-0,0003	0,0009
Momentum	21	13	0,4152	-1,6986	0,3271	-0,3335	-0,0003	0,0006	0,0004	0,0020
Multi-factor	183	44	-0,1434	-2,1135	-0,6152	-1,4983	-0,0013	0,0006	-0,0040	0,0035
Value	44	27	0,3507	-1,6256	0,2790	-0,4940	-0,0003	0,0003	0,0003	0,0018
Total	**465**	**202**								

Table 7b. Evaluating SB ETFs during periods of crisis; second variant against benchmark. Regression of each SB ETF against corresponding benchmark for a period of crisis defined as 2007-11-01 - 2009-03-01. Mean of each SB ETF category is calculated after conducting the regression to the mean of the corresponding group of benchmark. Table show, for each category, the Sharpe ratio, IR, alpha and betas. All columns titled Diff 95 represent the amount to be added or withdrawn from the value to the left, in order to get a 95% confidence interval.

GLOBAL

Strategy	# ETFs	Sharpe	Sharpe 10% quantile	Sharpe 90% quantile	IR	IR 10% quantile	IR 90% quantile	Alpha	Alpha diff 95	Alpha 10% quantile	Alpha 90% quantile	Beta	Beta diff 95	Beta 10% quantile	Beta 90% quantile
Dividends	33	-1,7410	-2,0690	-1,3884	-0,5901	-1,4857	0,7031	-0,0035	0,0014	-0,0058	0,0000	1,0418	0,0014	0,8627	1,2007
Equal	28	-1,3970	-1,7072	-1,0738	-0,0752	-0,8770	0,9583	0,0001	0,0009	-0,0017	0,0017	1,0511	0,0009	0,8776	1,1873
Fundamental	22	-1,4823	-1,7884	-1,0704	-0,1786	-1,0879	0,5220	-0,0008	0,0013	-0,0034	0,0017	1,0317	0,0013	0,8638	1,1957
Growth	26	-1,4784	-1,5841	-1,3431	-0,0165	-0,6331	0,7435	-0,0004	0,0004	-0,0018	0,0008	0,9692	0,0004	0,9335	1,0185
Momentum	13	-1,5457	-1,9426	-1,2457	-0,2405	-1,2627	0,9522	-0,0005	0,0012	-0,0025	0,0019	0,9440	0,0012	0,7791	1,0982
Multi-factor	41	-1,4201	-1,8230	-0,9861	-0,0946	-1,0842	0,8655	-0,0025	0,0015	-0,0051	0,0019	0,9247	0,0015	0,6803	1,1527
Value	27	-1,5765	-1,7908	-1,3295	-0,1931	-1,0490	0,4621	-0,0006	0,0006	-0,0023	0,0002	1,0282	0,0006	0,9260	1,1894
Total	190														

Table 7c. Evaluating SB ETFs during periods of crisis; first variant against FFCV factors. Regression of the mean of SB ETF categories against Fama French Carhart Volatility factors for a period of crisis defined as 2007-11-01 - 2009-03-01.

US

Strategy	# ETFs	# ETFs bad times	Sharpe	Sharpe bad times	Alpha	Alpha diff 95	Alpha bad times	Alpha diff 95 bad times	Ex Mkt	Ex Mkt diff 95	Ex Mkt bad times	Ex Mkt diff 95 bad times	HML	HML diff 95	HML bad times	HI 9 t
Dividends	19	14	0,2084	-1,9814	0,0001	0,0006	-0,0045	0,0027	0,7557	0,0372	0,8487	0,1318	0,2983	0,0422	0,3841	0
Equal	60	30	0,2623	-1,5698	-0,0002	0,0005	0,0011	0,0016	1,0847	0,0336	1,1683	0,0792	0,1227	0,0381	0,0770	0
Fundamental	40	16	0,3165	-1,6772	-0,0001	0,0005	-0,0002	0,0011	1,0011	0,0305	1,0090	0,0534	0,1156	0,0346	0,1100	0
Growth	37	25	0,1315	-1,6447	-0,0001	0,0003	0,0007	0,0015	1,0494	0,0200	1,1370	0,0744	-0,1725	0,0226	-0,0966	0
Momentum	16	11	0,4755	-1,6419	0,0001	0,0006	0,0012	0,0016	1,0034	0,0374	1,1243	0,0767	0,0305	0,0425	-0,0910	0
Multi-factor	105	40	-0,2423	-2,0433	-0,0005	0,0006	0,0000	0,0029	0,9548	0,0349	1,2185	0,1383	0,0635	0,0396	0,0151	0
Value	41	26	0,3934	-1,7242	0,0002	0,0003	-0,0008	0,0014	0,9225	0,0186	0,9876	0,0688	0,3751	0,0211	0,1899	0
Total	**318**	**162**														

Strategy	Mom	Mom diff 95	Mom bad times	Mom diff 95 bad times	SMB	SMB diff 95	SMB bad times	SMB diff 95 bad times	VIX corr.	VIX corr. Bad times	VIX	VIX diff 95	VIX bad times	VIX diff 95 bad times
Dividends	-0,0831	0,0267	-0,1892	0,1039	0,0260	0,0438	0,2814	0,1681	-0,5935	-0,7543	-0,0055	0,0069	0,0013	0,0323
Equal	-0,0124	0,0241	-0,0159	0,0625	0,2947	0,0395	0,1650	0,1010	-0,6216	-0,8116	0,0037	0,0063	0,0128	0,0194
Fundamental	-0,0528	0,0219	-0,0154	0,0421	0,2421	0,0359	0,1852	0,0681	-0,5019	-0,8059	0,0069	0,0057	0,0024	0,0131
Growth	0,0281	0,0143	0,0958	0,0586	0,2838	0,0235	0,2792	0,0948	-0,6040	-0,8067	0,0025	0,0037	0,0030	0,0182
Momentum	0,1301	0,0269	0,1124	0,0605	0,3039	0,0441	0,1834	0,0978	-0,5399	-0,7926	0,0002	0,0070	0,0159	0,0188
Multi-factor	0,0208	0,0251	0,0906	0,1090	0,2279	0,0410	0,2107	0,1763	-0,6034	-0,7653	-0,0009	0,0065	0,0292	0,0338
Value	-0,036	0,0134	-0,0979	0,0542	0,2834	0,0219	0,2663	0,0877	-0,6877	-0,8033	-0,0042	0,0035	0,0087	0,0168

Table 7d. Evaluating SB ETFs during periods of crisis; second variant against FFCV factors. Mean of each SB ETF category is calculated after conducting the regression of the SB ETF against Fama French Carhart Factors and Volatility for a period of crisis defined as 2007-11-01 - 2009-03-01. Table show, for each category, the Sharpe ratio, alpha, correlation and beta to VIX as well as betas to the FFC factors. All columns titled Diff 95 represent the amount to be added or withdrawn from the value to the left, in order to get a 95% confidence interval. VIX corr is correlation to volatility index. 10% quantile and 90% quantile is shown to the left of the mean and diff 95.

US

Strategy	# ETFs	Sharpe	Sharpe 10% quantile	Sharpe 90% quantile	Alpha	Alpha diff 95	Alpha 10% quantile	Alpha 90% quantile	Ex Mkt	Ex Mkt diff 95	Ex Mkt 10% quantile	Ex Mkt 90% quantile	HML	HML diff 95	HML 10% quantile	HML 90% quantile
Dividends	14	-1,6937	-1,8953	-1,4988	-0,0043	0,0025	-0,0097	-0,0003	0,8531	0,0025	0,6297	1,1090	0,4513	0,0025	0,0658	0,9554
Equal	30	-1,3267	-1,7038	-0,8000	0,0009	0,0013	-0,0040	0,0064	1,1535	0,0013	0,4561	2,1976	0,0544	0,0013	-0,3960	0,7723
Fundamental	15	-1,5602	-1,8270	-1,2319	-0,0004	0,0010	-0,0020	0,0022	1,0210	0,0010	0,8364	1,3717	0,0812	0,0010	-0,1499	0,3493
Growth	25	-1,6101	-1,7901	-1,4472	0,0010	0,0005	0,0003	0,0017	1,1691	0,0005	1,0187	1,2929	-0,1392	0,0005	-0,2438	0,0073
Momentum	11	-1,4841	-1,7943	-1,1496	0,0012	0,0015	-0,0016	0,0046	1,1051	0,0015	0,6318	1,8534	-0,0947	0,0015	-0,2924	0,1581
Multi-factor	39	-1,4532	-1,8325	-0,9859	0,0001	0,0015	-0,0010	0,0044	1,1453	0,0015	0,5320	1,9909	-0,0308	0,0015	-0,4143	0,2508
Value	26	-1,6615	-1,8757	-1,4556	-0,0008	0,0006	-0,0022	0,0005	0,9654	0,0006	0,8590	1,0955	0,2015	0,0006	-0,0096	0,3714
Total	160															

Strategy	# ETFs	Mom	Mom diff 95	Mom 10% quantile	Mom 90% quantile	SMB	SMB diff 95	SMB 10% quantile	SMB 90% quantile	VIX	VIX diff 95	VIX 10% quantile	VIX 90% quantile	VIX corr.	VIX corr. 10% quantile	VIX corr. 90% quantile
Dividends	14	-0,1127	0,0025	-0,2197	-0,0062	0,1962	0,0025	-0,1522	0,7767	-0,0048	0,0025	-0,0323	0,0121	-0,7322	-0,8057	-0,6271
Equal	30	-0,0178	0,0013	-0,4144	0,5054	0,1955	0,0013	-0,3795	0,8181	0,0050	0,0013	-0,0657	0,0819	-0,6943	-0,7878	-0,5948
Fundamental	15	-0,0278	0,0010	-0,1607	0,1239	0,2392	0,0010	-0,1864	0,7876	0,0086	0,0010	-0,0192	0,0417	-0,7573	-0,8271	-0,7219
Growth	25	0,0833	0,0005	0,0195	0,1810	0,2599	0,0005	-0,0296	0,6389	0,0074	0,0005	-0,0102	0,0182	-0,7855	-0,8179	-0,7337
Momentum	11	0,1089	0,0015	-0,1426	0,4498	0,2353	0,0015	-0,2643	0,5631	0,0102	0,0015	-0,0224	0,0464	-0,7086	-0,7755	-0,6015
Multi-factor	39	0,0641	0,0015	-0,2426	0,5684	0,2633	0,0015	-0,2326	0,7211	0,0196	0,0015	-0,0416	0,0933	-0,6629	-0,7840	-0,4474
Value	26	-0,1087	0,0006	-0,2681	-0,0130	0,2934	0,0006	-0,2211	0,8726	0,0039	0,0006	-0,0184	0,0451	-0,7769	-0,8370	-0,7085
Total	160															

Table 8a Mutual Funds. Display of the mutual funds with the most negative alpha (not necessarily with the lowest diff 95).

US

Fund	Alpha	Alpha diff 95	Dividends	Dividends diff 95	Equal	Equal diff 95	Fundamental	Fundamental diff 95	Growth	Growth diff 95
2777	-0,0018	0,0018	-0,4265	0,8232	0,1295	0,9304	-0,4294	1,3214	0,7887	0,7926
2785	-0,0018	0,0017	1,2215	0,6554	0,3138	0,5540	-1,1628	0,8695	0,5558	0,5768
2725	-0,0017	0,0014	0,5457	0,4972	-0,1834	0,4680	0,1524	0,7328	0,2834	0,4939
2807	-0,0017	0,0018	-0,4010	0,8191	0,1688	0,9258	-0,2812	1,3148	0,7344	0,7886
2757	-0,0017	0,0019	0,4729	0,8306	-0,5253	0,9584	-0,8025	1,3884	1,5625	0,8280
2758	-0,0017	0,0019	0,4971	0,8317	-0,5290	0,9596	-0,8247	1,3903	1,5667	0,8292
2804	-0,0017	0,0017	1,2190	0,6508	0,3086	0,5501	-1,1748	0,8635	0,5652	0,5727
3037	-0,0017	0,0011	0,5439	0,3863	-0,2042	0,3636	0,5310	0,5693	0,0384	0,3838
3038	-0,0017	0,0011	0,5176	0,3851	-0,2124	0,3625	0,5579	0,5676	0,0228	0,3826
3036	-0,0016	0,0011	0,5420	0,3832	-0,2053	0,3607	0,5403	0,5648	0,0391	0,3807
Mean	**-0,0003**		**0,1988**		**0,0328**		**0,1008**		**0,3340**	

Fund	Low Vol.	Low Vol. diff 95	Momentum	Mom diff 95	Multi-factor	Multi-factor diff 95	Value	Value diff 95
2777	0,2046	0,4657	-0,3450	0,6315	1,1853	0,7618	0,0116	1,1432
2785	0,5209	0,4268	0,0182	0,5153	-0,4322	0,4946	0,0737	0,6217
2725	-0,5099	0,3418	-0,0330	0,4241	0,0658	0,4294	0,6341	0,5096
2807	0,1837	0,4634	-0,3459	0,6283	1,1685	0,7580	-0,1082	1,1374
2757	-0,5278	0,4763	0,5682	0,6642	0,0586	0,7794	0,3991	1,1246
2758	-0,5257	0,4769	0,5987	0,6651	0,0104	0,7805	0,4047	1,1261
2804	0,5314	0,4238	-0,0013	0,5117	-0,4168	0,4911	0,0793	0,6173
3037	-0,3887	0,2655	-0,1564	0,3295	0,3625	0,3336	0,2416	0,3960
3038	-0,3724	0,2647	-0,1602	0,3285	0,3856	0,3326	0,2324	0,3948
3036	-0,3864	0,2634	-0,1639	0,3269	0,3602	0,3309	0,2457	0,3928
Mean	**-0,0656**		**-0,0743**		**0,1716**		**0,0278**	

Mutual Funds	
Negative alpha, not significant	58,72%
Significantly negative alpha	13,37%

Table 8b. Hedge funds. The hedge funds with a negative alpha.

GLOBAL

Fund	Alpha	Alpha diff 95	Dividends	Dividends, diff95	Equal	Equal, diff95	Fundamental	Fundamental, diff95	Growth	Growth, diff95
1526	-0,0054	0,0293	0,0790	0,4574	0,3223	0,5479	0,1544	0,3779	0,5781	0,3687
23 818	-0,0048	0,0228	-0,0155	0,8365	2,6563	2,8195	-1,9629	1,9520	-0,6176	1,8802
5227	-0,0045	0,0197	0,1817	0,3124	-0,0265	0,2986	-0,0270	0,2651	-0,0121	0,2607
16 179	-0,0042	0,0056	-0,1090	0,0910	-0,0949	0,0927	0,1868	0,1217	-0,2981	0,1968
5022	-0,0027	0,0100	0,0299	0,1372	-0,0103	0,1264	0,1279	0,1427	0,2855	0,1494
3087	-0,0021	0,0100	-0,0158	0,1451	0,0761	0,1361	-0,0203	0,1555	-0,4583	0,1669
19 980	-0,0009	0,0070	0,1435	0,2023	-0,1084	0,4637	0,0234	0,3985	0,5591	0,5093
Mean (of all 69)	0,0071		0,1013		0,2461		-0,0144		-0,1407	

Fund	Long/Short	Long/Short, diff95	Momentum	Momentum, diff95	Multi-factor	Multi-factor, diff95	Value	Value, diff95
1526	0,2121	0,6805	-0,8276	0,4399	0,0788	0,6510	-1,0444	0,7236
23 818	0,0822	0,4991	0,5790	2,0145	0,2056	0,7806	-1,0005	1,1619
5227	0,3863	0,5028	-0,0323	0,2946	0,5585	0,3826	-0,1385	0,4589
16 179	0,1472	0,1197	0,0355	0,0849	0,0106	0,1347	0,3525	0,2405
5022	-0,0562	0,2104	-0,0088	0,1168	0,1099	0,1812	-0,1623	0,2404
3087	-0,0608	0,2058	0,0487	0,1249	0,0088	0,1938	0,2012	0,2649
19 980	0,0938	0,1978	-0,0985	0,3991	-0,0496	0,3244	0,0258	0,3796
Mean (of all 69)	0,0968		0,0105		0,1101		-0,1745	

Table 9. SB ETFs as complement to self-constructed portfolio. Contribution of each SB ETF category to sharpe when added to a portfolio of 40% bonds and 60% equity. The table to the left displays the mean marginal Sharpe as well as the standard deviation. 10% quantile and 90% quantile is shown to the left of the mean and diff 95. The table to the right shows the number of SB ETFs in each category that contribute positively to Sharpe ratio.

US

Strategy	# ETFs
Dividends	5
Equal	15
Fundamental	11
Growth	10
Long/short	3
Low Vol.	8
Momentum	6
Multi-factor	21
Value	16
Total Pos	95
Total	249
Ratio Positive Marg. Sharpe:	38,15%

US

Strategy	# ETFs	Mean Marg. Sharpe	Std Marg. Sharpe	90% quantile	10% quantile
Dividends	16	-0,0069	0,0169	0,0144	-0,0320
Equal	44	-0,0083	0,0186	0,0198	-0,0319
Fundamental	30	-0,0023	0,0162	0,0190	-0,0176
Growth	35	-0,0082	0,0158	0,0167	-0,0277
Long/Short	5	0,0067	0,0144	0,0303	-0,0057
Low Volatility	7	0,0187	0,0050	0,0265	0,0128
Momentum	14	-0,0026	0,0160	0,0183	-0,0191
Multi-factor	60	-0,0081	0,0218	0,0191	-0,0368
Value	38	-0,0032	0,0137	0,0156	-0,0200