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# PERFORMANCE OF SMART BETA ETFS IN THE U.S. MARKET: 2009–2019


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## Abstract

**Purpose:** This paper empirically analyses the performance of smart beta exchange traded funds (ETFs) through the absolute return, relative return, and risk-adjusted return over the decade from 2009 to 2019.

**Methodology:** Using a sample of smart beta ETFs in the U.S. stock market, we examine the components of the risk factors in a smart beta strategy.

**Results:** Our results show that a smart beta strategy is not able to maintain a persistent performance over the period examined. Moreover, there is not a single year that smart beta ETFs could generate an abnormal return that is statistically significant. The evidence illustrates that returns of smart beta ETFs do not significantly beat the S&P 500 market benchmark on an absolute, relative, and risk-adjusted return basis.

**Keywords:** *Smart betas, Exchange traded funds, Excess returns, Risk-adjusted returns*

## 1. INTRODUCTION

Since 2000, exchange traded funds (ETF) products have become increasingly popular among investors in the financial markets. The first ETF was introduced in 1993, and it evolved to becoming an alternative investment to investors (Investment Company Institute, 2015). The original purpose of ETFs is to mimic the returns of an index (Bioy and Rose, 2012) such as Standard and Poor's Top 500 Index or S&P 500. Ten years later, smart beta (SB) ETFs have developed with the aim of generating abnormal returns. SB ETFs use a rule-based system to select stocks into a portfolio through the assignment of weights based on specific factors. They offer investors exposure to multiple factors compared to regular market-value index strategies. A smart beta strategy is a combination of passive and active strategies with the aim of exploiting the factors that can generate a positive return or minimize the portfolio's risks (Figure 1).

<Insert Figure 1 about here.>

The opportunity to trade ETFs on an organized stock exchange allows investors to manage their real-time price development (Securities and Exchange Commission, 2013). Moreover, ETFs provide investors with added exposure opportunities in commodities, currencies, bonds, and stocks. In this paper, however, we focus on ETFs with equities as their underlying assets. A number of media articles shows that the smart beta outperforms traditional investment.[1] Smart beta ETFs can be exposed to either a single or multiple factor. Morningstar (2019) reports that these strategies generate the highest returns, and U.S. SB ETFs include more than 70% of the global market SB ETFs with record flows into ETFs built on Morningstar indexes. Yet, there exists several criticisms of SB ETF investments on investing in smart Beta exchange traded funds for investors as it tends to be factor fading (Stevenson, 2019). These factors may not create the potential value and could involve data mining bias when using the algorithms to screen the factors as there are up to 82 statistically significant factors involved in data-mining bias. This is consistent with practitioners like Blackrock using the Aladdin risk platform to screen the factors, resulting in up to 1,000 factors that could not generate any real value to the portfolios. The Blackrock report also reviews the results of back-testing of SB ETFs that, over 10 years, more than 50% of the factors used have lost their significance. It projected that SB ETFs will reach $2.4 trillion by 2025.[2] According to Ang (2013), SB ETF strategies could be viewed as over-exposure to various unsystematic risks and over-dependence on asset allocation. Without understanding the complexities in the constituents of the indices, investors might find it difficult to fully apply such strategies to generate returns. Hence, it is essential to study whether SB ETF strategies are able to generate returns that beat the market in the light of more complex indexation and exposure to various unique factors. Since SB ETFs are considered alternatives to traditional ETFs for investors, assessing

[1] https://www.cnbc.com/2015/03/16/are-smart-beta-funds-intelligent-investments.html

[2] https://www.bloomberg.com/press-releases/2016-05-12/blackrock-projects-smart-beta-etf-assets-will-reach-1-trillion-globally-by-2020-and-2-4-trillion-by-2025

whether SB ETFs have the potential to generate value to investors is of utmost importance in the long-term.

This paper tests the ability of SB ETFs to generate abnormal returns as well as outstanding performance relative to its own benchmark. This is done by comparing the performance between SB ETFs and the market. We also investigate the characteristics of SB ETF strategies that are able to persistently create higher risk-adjusted returns to investors over time and explain the risk compositions that are involved in generating the returns. We apply Carhart's (1997) extended Fama-French 3-factors model into a 4-factor one to explain and capture the pattern of investor behavior in a smart beta strategy. It is the objective of this paper to help investors understand the risk components accompanying the returns and to justify the utilization of a SB ETF investment strategy.

The remainder of the paper is organized as follows. Section 2 reviews the literature, section 3 develops our hypotheses, and describes the sample data and research methodology. Section 4 presents our findings and discusses the empirical results. Section 5 concludes.

## 2. LITERATURE REVIEW

The U.S.A. is the largest market for smart beta ETFs. Over the period 2010–2019, SB ETFs grew by 45% or around $797 bn (Figure 2). The U.S. and Europe are the primary (88.5%) and secondary (7.2%) market leaders in such market. However, there is a decline in the growth rate of new SB ETF products in those two regions by 0.6% and -4.8%, respectively, year-on-year. In the Asia-Pacific market, there is a significantly increase in total ETFs based on assets under management by 12.1% annually as revealed by Morningstar (Figure 3).

<Insert Figure 2 about here.>

<Insert Figure 3 about here.>

In the U.S., SB ETFs started in 2000 after the introduction of iShares Russell 100 Value IWD and iShares Russell 1000 Growth IWF. The total aggregate growth of this asset class comes from net inflows (78%) and appreciation of the assets (22%). The smart (strategic) beta market share has grown at a faster pace than the traditional ETFs. After 2015, that the growth rate of SB ETFs started to decline and remained around 21.5% of the overall ETF market in the U.S. due to a decrease in net inflow as providers faced challenges in differentiating among the various strategies and products, coupled with the lack of new strategic factors (Figure 4).

<Insert Figure 4 about here.>

Even though there is a decline in the growth of SB ETFs, the number of surviving SB ETFs since 2015 remains significant (Figure 5). In the more recent high volatility environment prior to 2020, SB ETFs continued to gain popularity as they provide a customized exposure to equities based on individual risk preference. The three popular

SB strategies are based on value, growth, and dividends, which account for 25.1%, 23.9%, and 6.4% of the total market share of all SB ETFS in the U.S. (Figure 6).

<Insert Figure 5 about here.>

<Insert Figure 6 about here.>

Smart beta ETFs started from the evolution of indexing fund strategies used to diversify investors' portfolios. According to Alford (2017), in a Goldman Sachs report, there remains an unclear delineation between passive and active SB ETF strategies. On one hand, they are passive in the sense that they track an index. However, at the same time, they appear to be deviate by weighting the underlying assets differently from the market capitalization of their benchmark indices, in the hope of making a higher return. Moreover, the goals of traditional ETFs and SB ETFs are different. The former aims to follow the development of the index while the latter aims to generate risk-adjusted excess returns relative to a benchmark index at a lower cost compared to a regular active strategy.

Several papers in the literature claim that the cost of implementing a SB strategy is lower than that of an active strategy. Jacobs and Levy (2014) find that a SB strategy rebalances the portfolio periodically, contributing to a negative return. Johnson, Bioy, and Boyadzhiev (2016) find that the transaction costs incurred from portfolio replication vary across regions and tend to increase remarkably through time, posing a grave challenge to fund managers aiming to beat the market return. Ratcliffe, Miranda, and Ang (2017), using a transaction cost model, report that the cost of a SB strategy would eliminate any return premium.

In this paper, however, we focus on the returns of SB strategies that have led to several controversial issues. Kahn and Lemmon (2014) believe that a smart beta strategy comes from those investors who do not believe that the market is efficient. Such a strategy is suitable for investors who can identify the factors that can generate risk-adjusted return over the benchmark. Many investors can take advantage of the higher returns by diversifying their portfolio through investing in a range of factors. Hsu, Kalesnik, and Li (2012) replicate smart beta strategies under both the risk-aware (or minimum-variance) portfolio environment and one that does not involve volatility control for 1,000 large stocks. They find that a SB strategy can generate excess returns and outperform a traditional ETF in terms of both the Sharpe ratio and the Information ratio. In addition, Richard and Roncalli (2015) has applied a SB strategy to four different models—equal risk contribution (ERC), risk-based global minimum variance (GMV) portfolio, most diversified portfolio (MDP), and equally weighted (EW) portfolio—to compare their volatility and excess returns. They find that SB strategies can provide a better performance, especially during an economic downturn. SB strategies are also transparent in providing investors with their weighting factors. Practitioners like Morningstar (2014) have tested this by heavily weighting them with different single factors, such as volatility, and find that SB strategies can generate a higher return with a lower risk.

In contrast, Glushkov (2015) finds that SB ETFs do not outperform its benchmark on a risk-adjusted basis due to the unintended-expose factor which outweighs its positive return. His conclusion is based on a sample of 164 SB ETFs in 2003–2014. He also finds that SB strategies do not perform well throughout all market environments as they do not provide a well-diversified portfolio compared to traditional ETFs (passive strategy). Jacobs (2015) supports Glushkov's observation that it is not possible to control the increase in the number of factors-trying and an inability to limit the investments. This may lead to factor crashes from a popular to underperforming factors. SB ETF strategies commonly utilize value, growth, momentum, and size factors, which Bender et al. (2013) claim can be treated as a group of stocks that can explain both risk and return. From their analysis of MSCI factor indices, using data from 1996–2012, weighting these factors can outperform an equally-weighted market portfolio.

Fama and French (1992) use size and value factors to generate excess returns between 1962–1989. However, Ang (2013) claims that during the financial crisis of 2008, the returns of these factors are lower than MSCI market index returns. He explains that these factors can disappear through the market cycle, which is consistent with Jacobs' (2015) argument. Even though these factors perform well over the long run, it may be because investors are compensated for bearing the risk during a recession. However, Green, Hand, and Zhang (2014) argue that the reason that SB ETFs do not appear to outperform risk-adjusted portfolios is due to the limited number of factors that are able to provide a significant result. Moreover, Fuller, Giovinazzo, and Tung (2014) contend that SB ETFs are not a good alternative to active investment strategies, which have multiple factors to generate diversification benefits to investors. Furthermore, SB ETFs require more frequent follow-up work by their managers than traditional ETFs.

Since SB ETFs are an alternative investment tool for investors, by considering the Efficient Market Hypothesis, many consider a SB ETF strategy as being able to generate a higher risk-adjusted return to their portfolios. In this paper, we examine both absolute and relative returns of SB ETFs and compare them with the benchmark to see whether the returns generated under a SB is statistically significance. However, controversies exist on the choice of an appropriate benchmark. According to Cai et al. (2018), stock indices are normally used as the benchmark since the fundamental purpose of SB ETFs is to earn a higher return than a capitalization-weighted index. In this paper, we apply the S&P 500 index as the benchmark.

Fong (2005) claims that size and value are not significant factors in an index; however, if these factors are considered in portfolio weights, positive abnormal returns would be generated. This finding is consistent with those of Black (1993), who reports that value strategies can generate excess return, in line with the Fama-French (2007) model. Strauts (2013) also finds that including a momentum factor into the portfolio can generate excess returns.

Studies have shown that investors tend to either overreact (Barberis, Shleifer, & Vishny, 1998) or under-react (Hong, Lim, & Stein, 2000) to news that can lead to a momentum effect. To illustrate, under-reaction is when investors do not react quickly enough to news about market shares, causing the price to deviate from the real value (Edwards, 1968). In his experiment, he finds that the perception is updated in the right direction, but that the speed of the change is not as rapid as in rational events. Such a delay in the price increase can cause one momentum strategy to yield positive returns. They also show that under-reaction occurs only in the short term and then overreaction happens in the longer term. Over-reaction occurs when investors are overwhelmed by excessive positive and continuous growth of the company over a long period, leading to investors being less aware of negative news.

## 3. HYPOTHESES, DATA, AND METHODOLOGY

### 3.1 Hypotheses

Our hypotheses are based on the work of Hsu, Kalesnik, and Li (2012) and Richard and Roncalli (2015) who find that smart beta strategies provide a higher excess return even during periods of economic downturn. We also draw on the findings of Jacobs (2015) that returns from smart beta strategies do not consistently outperform the market over time. We test the following two hypotheses:

Hypothesis 1: Return of SB ETFs > Return of benchmark

Hypothesis 2: Sharpe ratio of SB ETFs > Sharpe ratio of benchmark

Fong (2005) and Strauts (2013) report that investing in size, value, and momentum factors can generate abnormal returns. They find that, even during a market downturn, such investments continue their good performance based on risk-adjusted returns. Following Carhart (1997), the *size factor*, SMB (or small minus big), is quantified by the spread of the returns between small and big firms measured by their market capitalization. The *value factor*, HML (or high minus low), accounts for the spread in returns between value and growth stocks. Value stocks are defined as those with a high book-to-market ratio, and growth stocks, those with a low book-to-market ratio. The *momentum factor*, UMD (or up minus down), represents the spread of the returns between the winning and losing momentum. A stock is deemed to have a winning momentum if its prior 12-month average return is positive, and losing momentum, if negative. These factors in Carhart's (1997) model are expected to be positive, and hypotheses 3–7 are expected to hold.

Hypothesis 3: Alpha of SB ETFs > 0

Hypothesis 4: Beta MRP of SB ETFs > 0

Hypothesis 5: Beta SMB of SB ETFs > 0

Hypothesis 6: Beta HML of SB ETFs > 0

Hypothesis 7: Beta UMD of SB ETFs > 0

### 3.2 Data

Annual and monthly returns from 2009 to 2019 are obtained from Morningstar for both the SB ETFs and benchmark S&P 500 index to test our hypotheses. We select the largest U.S. SB ETFs that have total assets under management (AUM) of around 60% of the all SB ETFs in the U.S. market that also meet certain selection criteria.[3] The nine largest funds are Vanguard Growth ETF, Invesco S&P 500 Revenue ETF, Vanguard Value ETF, Vanguard Mid-Cap Growth ETF, Invesco S&P MidCap 400 Revenue ETF, Vanguard Small-Cap Growth ETF, Invesco S&P SmallCap 600 Revenue ETF, Vanguard Small-Cap Value ETF, and Invesco Defensive Equity ETF. These ETFs are described in Table 1.

<Insert Table 1 about here.>

The nine selected SB ETFs must meet the following selection criteria. (1) They must have at least 90% of their assets invested in U.S. equities. (2) The selected funds must not contain any structured agreements or any derivative instruments that that might have an impact on their returns. (3) The funds must have a corresponding S&P tracking index that can be used as an appropriate benchmark. (4) Lastly, the selected funds must have an inception date that is at least 10 years before 2019 to facilitate the examination of any persistent trends. The funds, together with their corresponding tracking indices, are shown in Table 2.

<Insert Table 2 about here.>

We compute SMB (small minus big) by taking the average return of three small portfolios and subtracting the average return of three big portfolios:

$$SMB = \frac{1}{3}(Small\ Value + Small\ Neutral + Small\ Growth) - \frac{1}{3}(Big\ Value + Big\ Neutral + Big\ Growth) \qquad (1)$$

HML (high minus low) is the average return of two value portfolios minus the average return of two growth portfolios:

$$HML = \frac{1}{2}(Small\ Value + Big\ Value) - \frac{1}{2}(Small\ Growth + Big\ Growth) \qquad (2)$$

UMD (up minus down) is the average return of two prior high return portfolios minus the average return of two prior low return portfolios:

$$UMD = \frac{1}{2}(Small\ High + Big\ High) - \frac{1}{2}(Small\ Low + Big\ Low) \qquad (3)$$

### 3.3 Methodology

To test our hypotheses, we examine the absolute returns of SB ETFs and the relative returns of SB ETFs against the S&P 500 benchmark to form a paired t-test to uncover whether statistically significant SB ETF returns have been generated. We further apply t-tests on the Sharpe ratio of SB ETFs and their relevant benchmarks to reveal any

[3] https://etfdb.com/2009/size-does-matter-to-a-point-study-of-etf-liquidity/.

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statistically significant risk-adjusted SB ETF returns. We use both absolute and relative returns to analyze the performance of SB ETFs over the period 2009–2019. Absolute returns are the actual returns of the SB ETFs, while relative returns are the differences between the absolute returns and the benchmark (S&P 500). The Sharpe Ratio is computed as:

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p} \tag{4}$$

where $R_p$ is the excess annual return of the SB ETFs, $R_f$ is the U.S. 3-month treasury bill rate, and $\sigma_p$ is the standard deviation of the monthly returns of the SB ETFs over the period.

We examine the risk factor composition in Carhart's (1997) four-factor model to explain the returns of our selected SB ETFs. We utilize the monthly returns of the component stocks within each ETF to arrive at the size factor (SMB), the value factor (HML), and the momentum factor (UMD) for each fund. The expected return of the SB ETF is computed as:

$$E\left(r_{i,t}\right) = r_f + \beta_{i,t}\left[E\left(r_{m,t}\right) - r_f\right] + \beta_{SMB,t}SMB_{j,t} + \beta_{HML,t}HML_{j,t} + \beta_{UMD,t}UMD_{j,t} \tag{5}$$

where $E\left(r_{i,t}\right)$ is the expected return of fund *i* in period *t*, $r_f$ is the U.S. 3-month treasury bill rate, $E(r_m, t)$ is the expected return of the market in period *t*, $\beta_{i,t}$ captures the risk exposure of the stocks to fund *i* in period *t*, $\beta_{SMB,t}$ captures the risk exposure due the size factor in the stocks, $\beta_{HML,t}$ captures the risk exposure due the value factor in the stocks, $\beta_{UMD,t}$ captures the risk exposure due the momentum factor in the stocks, and $SMB_{j,t}$, $HML_{j,t}$, and $UMD_{j,t}$ are as earlier defined for stocks *j* in fund *i* over the period *t*. A least squares regression is then run for each year from 2009 to 2019 to examine the persistence of the performance of SB ETFs over time.

## 4. EMPIRICAL FINDINGS AND DISCUSSION OF RESULTS

We report our findings of the nine SB ETFs that are among the largest in the U.S. in terms of their assets under management and compare their returns against those of the S&P 500 benchmark. Table 3 provides the average geometric return, standard deviation of returns, correlation between the returns of the SB ETFs and the S&P 500 benchmark returns, and the Sharpe ratio across the investment horizons of 4, 7, and 11 years.

<Insert Table 3 about here.>

From Table 3, we note that the excess returns of the SB ETFs over the market benchmark becomes smaller as the investment horizon becomes longer. Moreover, the correlation between the returns of the SB ETFs and those of the market index in each investment horizon is nearly one. Yet, the value of the Sharpe ratio declines sharply when the investment horizon lengthens, compared to the benchmark S&P 500. While the volatility of the SB ETFs is observed to increase with the length of the investment horizon, the risk-adjusted excess returns, as measured by the Sharpe ratio, has declined. The average excess monthly return declines from 2% to 1% from 4 to 11 years investment horizon, starting from 2009.

### 4.1 Performance of Smart Beta ETFs

Table 4 presents the average geometric percentage return, standard deviation of returns, the correlation between the returns of the SB ETFs and that of the market benchmark, and the Sharpe ratio for each year from 2009 to 2019. The average geometric return of SB ETFs is below that of the benchmark S&P 500 in five of the 11 years. The standard deviation of SB ETFs returns, however, is mostly higher than that of the S&P 500 except in 2015 when it is marginally lower. We note that SB ETFs perform poorly during an economic downturn, such as in 2018, when they achieved a negative return of –8.40% compared to the market's –5.03%. The results also show that the annualized returns of SB ETFs have a strong positive correlation with a maximum of 0.99 and a minimum of 0.90 over the period 2009–2019 even though 2010 is the only year that all SB ETFs have significantly outperformed the benchmark. Moreover, it is observed that the return of SB ETFs is extreme on both its upside and downside. Given that the standard deviation of SB ETF returns is higher than the benchmark's, the returns that SB ETFs generate do not always beat the S&P 500 in each period from 2009–2019 as shown by the excess returns in Table 4. Our findings are contrary to those of Hsu, Kalesnik, and Li (2012) and Richard and Roncalli (2015).

<Insert Table 4 about here.>

In addition, we analyze the persistence of the performance of SB ETFs from their excess returns over the S&P 500 benchmark in 2009–2019 on a monthly and annual basis to observe its trend. From its historical performance shown in Figures 7 and 8, we observe that the excess returns of SB ETFs over the benchmark S&P 500 have return characteristics that are similar to the fluctuations in monthly returns. As shown in Table 5, the mean excess annual return of SB ETFs above the benchmark returns is 1.04% compared to the average monthly excess return from 2009–2019 of 0.83%. The t-test results from Table 5, which are based on the assumption of equally weighted portfolios, provide evidence that both the annual and monthly returns of the SB ETFs do not beat the S&P 500 benchmark portfolio at a statistically significant level. The results show that the SB ETFs have a higher standard deviation of returns than that of the S&P 500. However, the returns of the SB ETFs are not consistent with their higher risk. This can be attributed to the size and efficiency of the U.S. stock market that makes it difficult for fund managers to search for positive alphas or abnormal returns.

<Insert Figure 7 about here.>

<Insert Figure 8 about here.>

<Insert Table 5 about here.>

We make use of the Sharpe ratio to measure the risk-adjusted performance of the

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SB ETFs. Table 6 shows that the average annual Sharpe ratio of 1.17 is lower than the market benchmark's ratio of 1.4. This implies that, even though the historical volatility of SB ETFs is higher than that of the benchmark, SB ETFs do not generate a higher risk-adjusted return. The lower average Sharpe ratio of the SB ETFs indicates that SB ETFs are likely to fail to beat the market, on average. In line with the annual Sharpe ratios shown in Table 4, we note the underperformance of SB ETFs relative to the market benchmark from 2012 to 2019, except for 2016 when they are about equal. With the extra risk that investors take in investing in a SB strategy, their resultant risk-adjusted returns are not significantly higher but, rather, are often lower that the market's. We therefore conclude that investing in SB ETFs may not be as "smart" as claimed.

<Insert Table 6 about here.>

Based on the historical performance of SB ETFs (see Tables 3 and 4), it appears that the *smartness* of SB ETFs has eroded over time. Going forward, SB ETFs, in general, may not be as good an investment strategy as previously thought. In fact, they may even earn a negative risk-adjusted return. In addition, according to Morningstar (2019), SB ETFs continue to have similar characteristics as stocks—i.e., with negatively-skewed returns (Fama and French, 2007), implying that SB ETFs may provide only a small gain but a higher probability of a negative returns. We explore in greater detail the risk-return characteristics of SB ETFs in the next sub-section.

### 4.2 Alpha and Risk Factors of Smart Beta ETFs

From the results presented in Table 7, the abnormal risk-adjusted return or Alpha that is generated from SB ETFs is insignificant, at any level of significance, in all years 2009–2019 and across the entire period. This means that SB ETF strategies may not be suitable for active investors looking to achieve active returns through time. We have applied Carhart's (1997) four-factor model to analyze the risk factors that generate SB ETF returns through running the least-squares regression model shown in Equation (5). The results in Table 7 show that the R-squares of the regression are above 90% in all years during the period 2009–2019 except for 2017 and 2019 when they are above 70%. Across the entire period, the $R^2$ is at 90%.

<Insert Table 7 about here.>

The results show that the market risk premium is the most consistent in contributing to the generating of abnormal returns. The *SMB* factor is shown to contribute negatively to abnormal returns. The *HML* factor largely contributes positively to abnormal returns, while the *UMD* factor, though mainly positive, is the least consistent in contributing to abnormal returns. The findings imply that the risk-adjusted returns do not persist over time.

Our findings imply that the market risk component is an important factor in generating the returns of SB ETFs. The coefficient of the market risk premium is positively significant at the 99% level in all years. Over the 2009–2019 investment horizon, this factor has a statistically positive impact on the expected return of SB ETFs at greater than the 99% confidence level. It is the only factor that is positive, at the 95%

significant level, in each and every year of the investment horizon. Investors with a similar risk profile as the market portfolio would do well to follow such a strategy. This also corresponds to the high correlation between returns of the SB ETFs and the S&P 500 index described in Table 3. However, there is no evidence to show that SB ETFs can consistently beat the benchmark over time.

During the entire period of 2009–2019, the size factor (*SMB*) shows a negative coefficient which is statistically significant at the 99% level. The coefficient of *SMB* is negative and mostly significant at the 99% level in all years except for 2017 and 2019. This implies that small-sized firms do not provide an excess return. In each of the years from 2009 to 2016, the *SMB* regression coefficient is significantly negative at the 99% level. It remains negative but not significant in 2017 and 2019. It appears that there is a discount in holding small companies' stock and that the size factor effect is becoming less significant in recent years. Investors can no longer expect that they would be compensated for holding small companies. Importantly, we note that there is not a single year whereby the size factor has a positive coefficient. As such, one might expect SB ETFs to invest less in small companies over time.

The coefficient of *HML* is positively significant in seven out of the 11 years, negatively significant in two years, and insignificant in two years. Importantly, the value effect, as measured by the regression coefficient of *HML*, is positively significant over the entire 2009–2019 period. However, the results are not consistent over time. The coefficient is significantly negative (at the 99% level) in 2010 and 2012, and not significant at any level in 2013 and 2019. It appears that there is some evidence of a value premium even though such a premium may not always be significant or consistent.

The momentum effect is captured by the factor *UMD* in our regression. The coefficient of *UMD* is positively significant (at the 90% level or higher) in five of the 11 years, negatively significant (at the 90% level) in two years, and insignificant (at the 90% level) in four years. Overall, though significantly positive across the entire 2009–2019 period, its coefficient fluctuates inconsistently on an annual basis. It is significantly negative (at the 90% level) in 2011 and 2016; significantly positive (at the 90% level or higher) in 2010, 2013, 2014, 2017, and 2018; and insignificant in the remaining four years. The momentum factor is thus deemed to be an inconsistent generator of returns for SB ETFs.

All the risk factors in Carhart's (1997) four-factor model, together with the Alpha, show statistical significance at the 99% confidence level across the entire period of the study although the results in a given year are not always be significant or have a consistent sign. This implies that the risk factors in the model can, to some extent, explain the returns of the SB ETFs. Alpha is not significant in any given year even though it is negatively significant across the entire period of study. Moreover, Alpha only has a positive sign in two out of the 11 years. This means that SB strategies not only fail to generate a significant positive excess return, they generate a return that is statistically below the market across the entire period of the study.

Among the four risk factors examined, the market risk, value, and momentum factors provide a premium to SB ETF returns. The size factor is the only one that provides a discount to SB ETF returns. These findings are thus unsatisfactory to investors searching for excess returns using a SB ETF strategy above what the market can offer. Our study has shown that SB ETF strategies may end up generating statistically negative returns instead. As such, SB strategies are not effective in achieving investors' expectations.

## 5. CONCLUSION

This paper provides an empirical analysis of the performance of smart beta (SB) ETFs in the U.S. market in terms of their absolute and relative returns, the risk-adjusted returns, as well as the risk factors to which SB ETFs are exposed from 2009 to 2019. The evidence provided in this study do not support the idea that SB ETFs can generate significantly positive risk-adjusted returns. Investors searching for a positive Alpha would be disappointed. On a risk-adjusted basis, the returns of SB ETFs are not significantly higher than that of the market benchmark. In fact, Alpha is found to be significantly negative. This conclusion is consistent with the Sharpe ratio given its reduced performance over time.

The results from our regression analysis reveal that the size factor contributes negatively to the returns of SB ETFs. However, the expected returns of SB ETFs are positively impacted by the market risk factor, the value factor, and the momentum factor. Overall, we find that smart beta strategies fail to generate significantly positive abnormal returns over time. This finding may be attributable to the highly efficient U.S. stock market, leaving no room for smart beta strategies to generate excess returns. With continuing technological advances and artificial intelligence, future new "smart" strategies may be developed. For now, however, it appears that smart beta strategies are not as smart as claimed.

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**APPENDIX**

The auto-correlation test shows that there is no issue with our sample data based on the consistent mean in Figure 1 and constant volatility in Figure 2, computed using the R program, which is appropriately applied in our model.

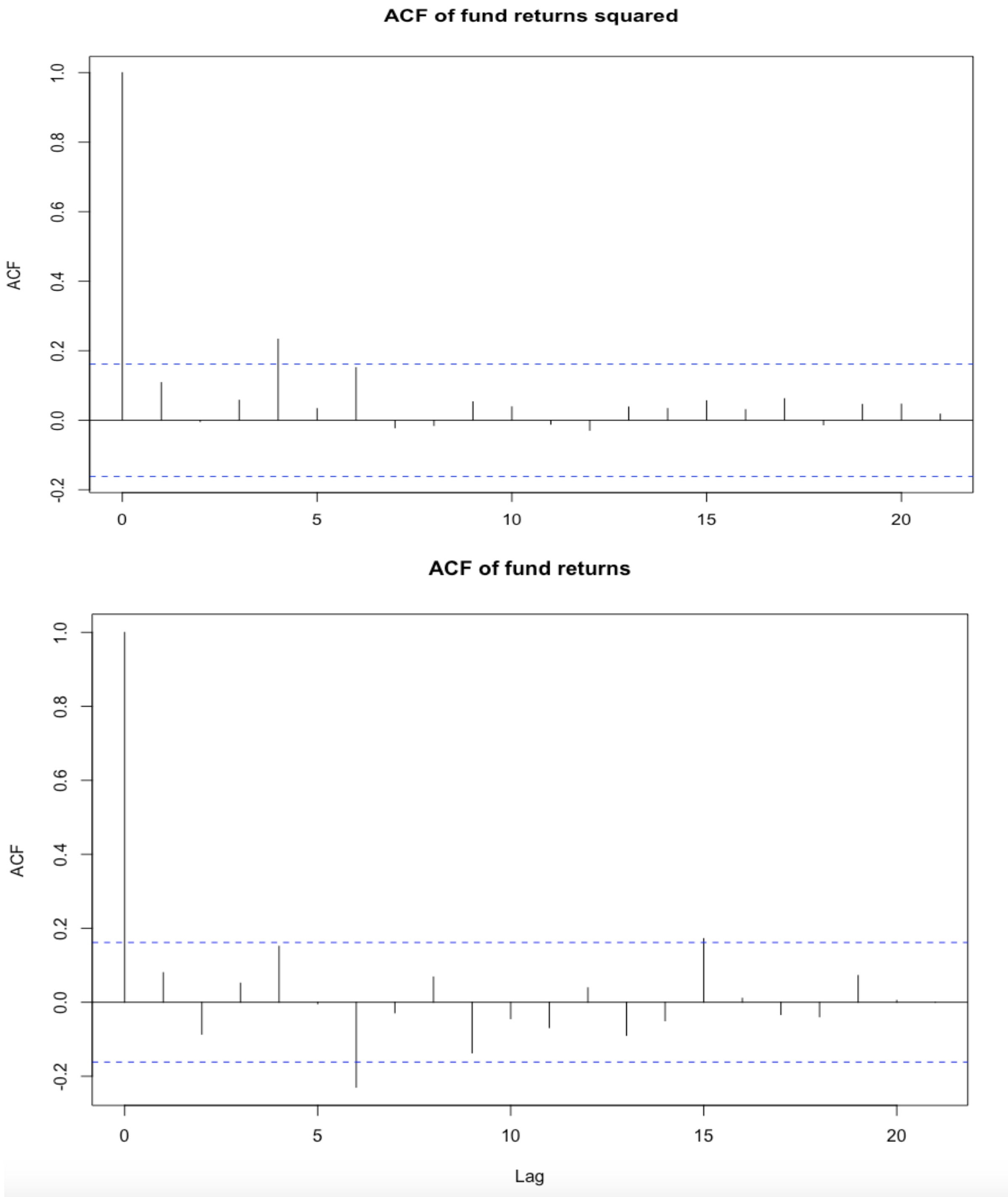

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**Figure 1**. Illustration of Smart Beta Strategy

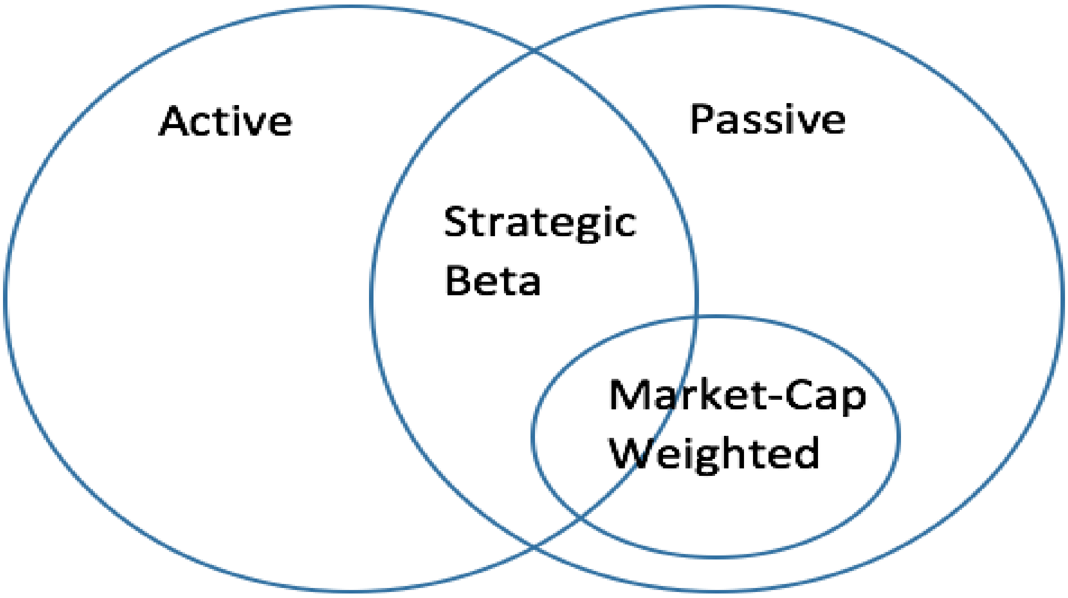

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**Figure 2**. Smart Beta Exchange Traded Funds' Net AUM of U.S. Markets, Morningstar

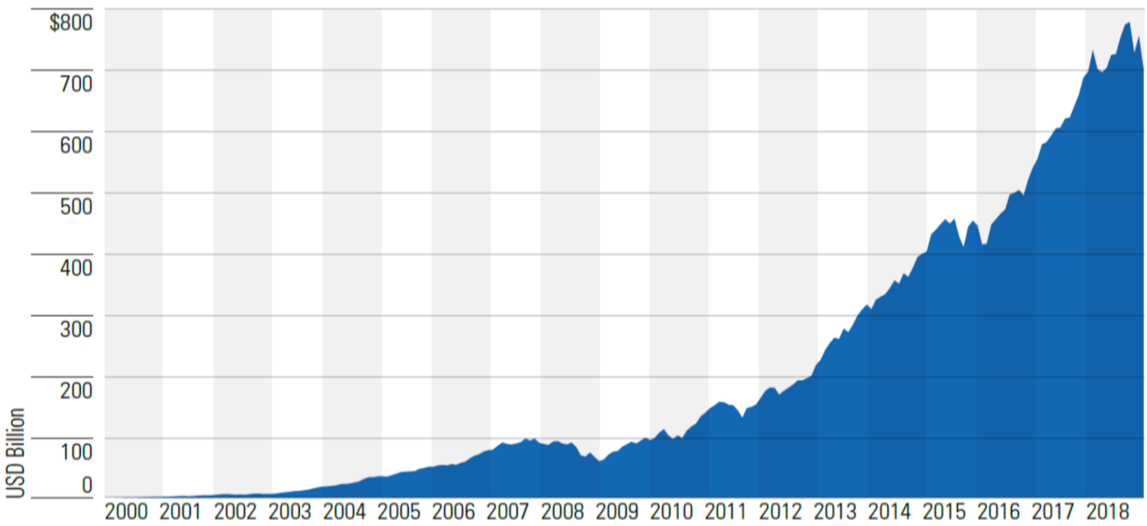


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**Figure 3**. Total Exchange-Traded Products Based on Assets Under Management

| | Assets 2018 (USD Bil) | Global Market Share (%) | Assets 2017 (USD Bil) | One-Year % Change | 2018 Flows (USD Bil) | As a % of Beginning AUM | # of ETPs 12/2018 | # of ETPs 12/2017 | One-Year % Change |
|---|---|---|---|---|---|---|---|---|---|
| U.S. | 705.1 | 88.5 | 700.6 | 0.6 | 74.4 | 10.6 | 693 | 634 | 9.3 |
| Canada | 10.1 | 1.3 | 10.61 | -4.5 | 1.3 | 11.9 | 182 | 162 | 12.3 |
| Europe | 57.4 | 7.2 | 60.3 | -4.8 | 5.0 | 8.2 | 409 | 389 | 5.1 |
| Asia-Pacific | 23.7 | 3.0 | 21.1 | 12.1 | 6.3 | 29.8 | 190 | 157 | 21.0 |
| Emerging Mkts | 0.8 | 0.1 | 0.9 | -9.1 | 0.1 | 10.5 | 19 | 19 | 0.0 |
| **Total** | **797.1** | **100** | **793.5** | **0.5** | **87.0** | **10.9** | **1,493** | **1,361** | **9.7** |

*Source*: Morningstar, 2019.

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**Figure 4**. Growth of Smart Beta Exchange Traded Products in the U.S.

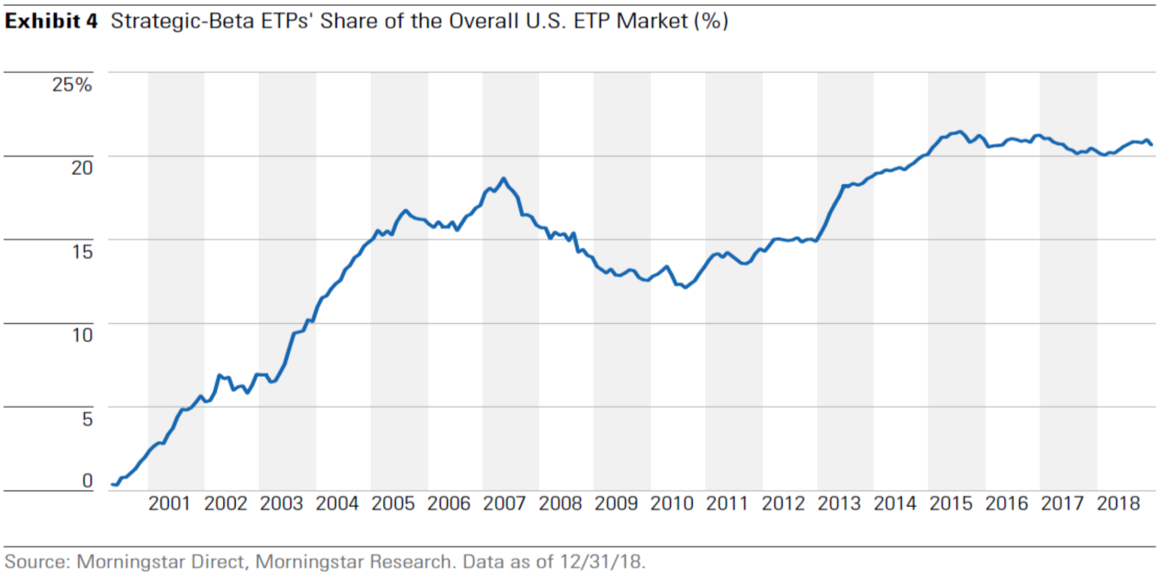

**Figure 5**. The number of surviving U.S. Smart Beta ETPs

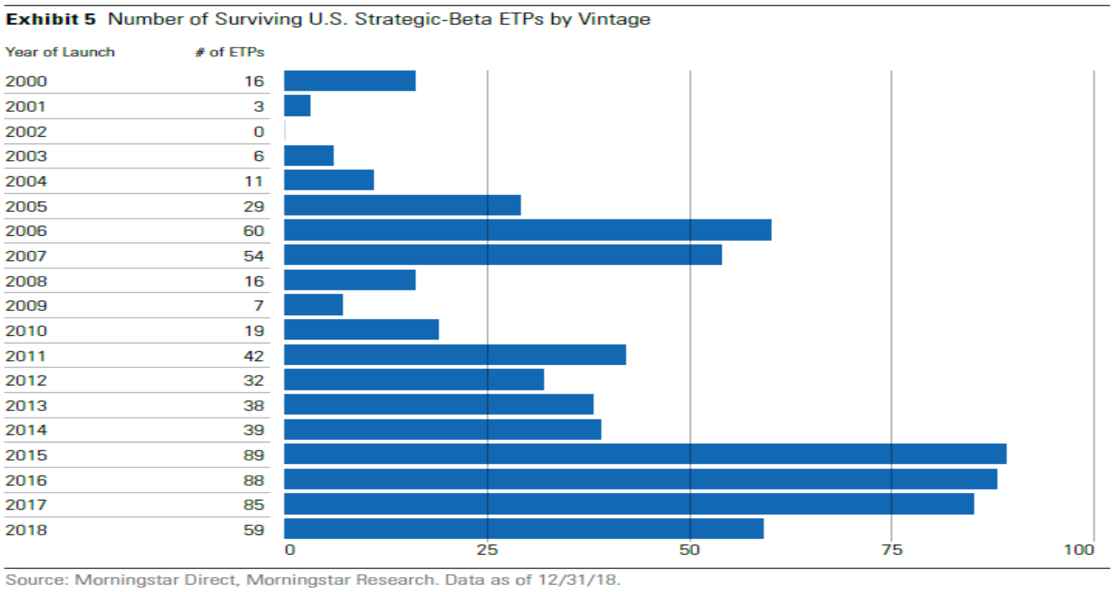

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**Figure 6**. The Factors Strategies of Smart Beta ETFs

| Strategic-Beta Group | # of ETPs | Assets (USD Bil) | % of Assets | 2018 Flows (USD Bil) | % of 2018 Gross Flows |
|---|---|---|---|---|---|
| Value | 53 | 176.9 | 25.1 | 23.9 | 31.4 |
| Growth | 40 | 168.8 | 23.9 | 13.8 | 18.2 |
| Dividend | 141 | 166.6 | 23.6 | 6.4 | 8.4 |
| Risk-Oriented | 57 | 55.1 | 7.8 | 9.9 | 12.9 |
| Multifactor | 171 | 42.8 | 6.1 | 9.8 | 12.9 |
| Fundamentals | 32 | 29.1 | 4.1 | 4.6 | 6.1 |
| Other | 66 | 23.7 | 3.4 | 0.3 | 0.4 |
| Momentum | 41 | 15.4 | 2.2 | 2.9 | 3.9 |
| Quality | 17 | 11.5 | 1.6 | 4.4 | 5.8 |
| Fixed Income | 42 | 9.5 | 1.3 | -1.1 | — |
| Commodity | 33 | 5.8 | 0.8 | -0.6 | — |

*Source*: Morningstar, 2019.

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**Figure 7**. The Average Monthly Excess return of Smart Beta ETFs over S&P 500

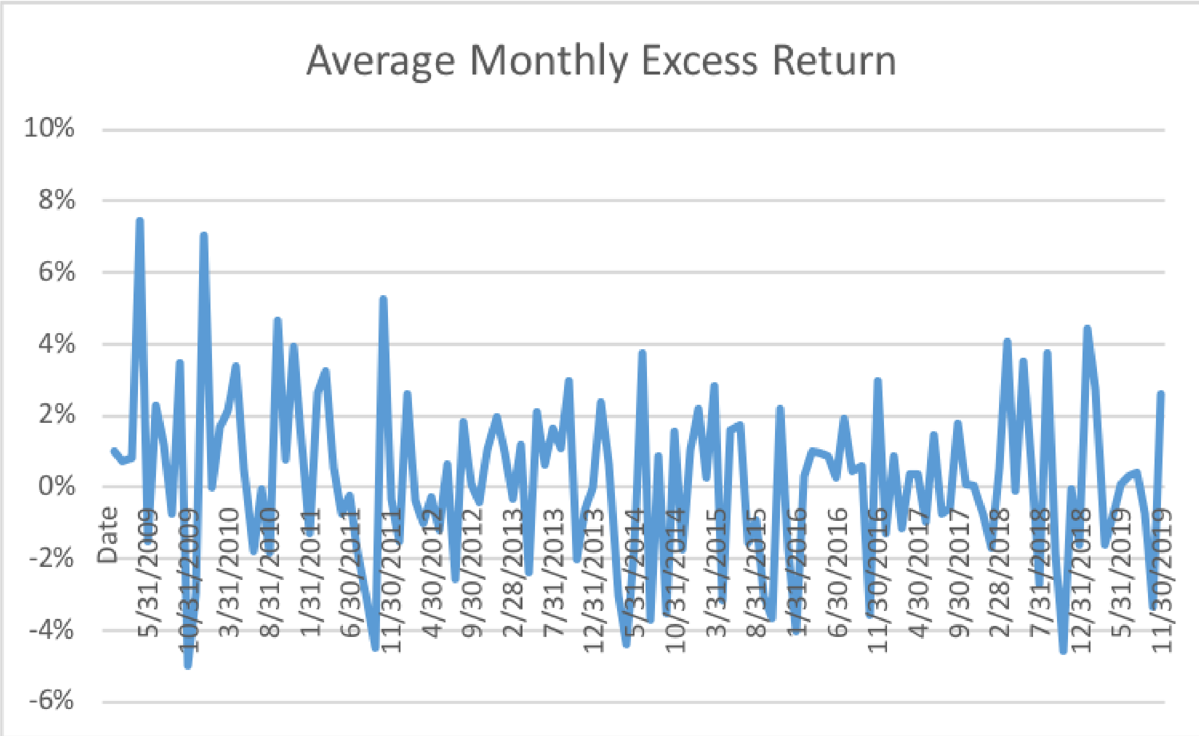

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**Figure 8**. The Annual Return comparison between Smart Beta ETFs and S&P500

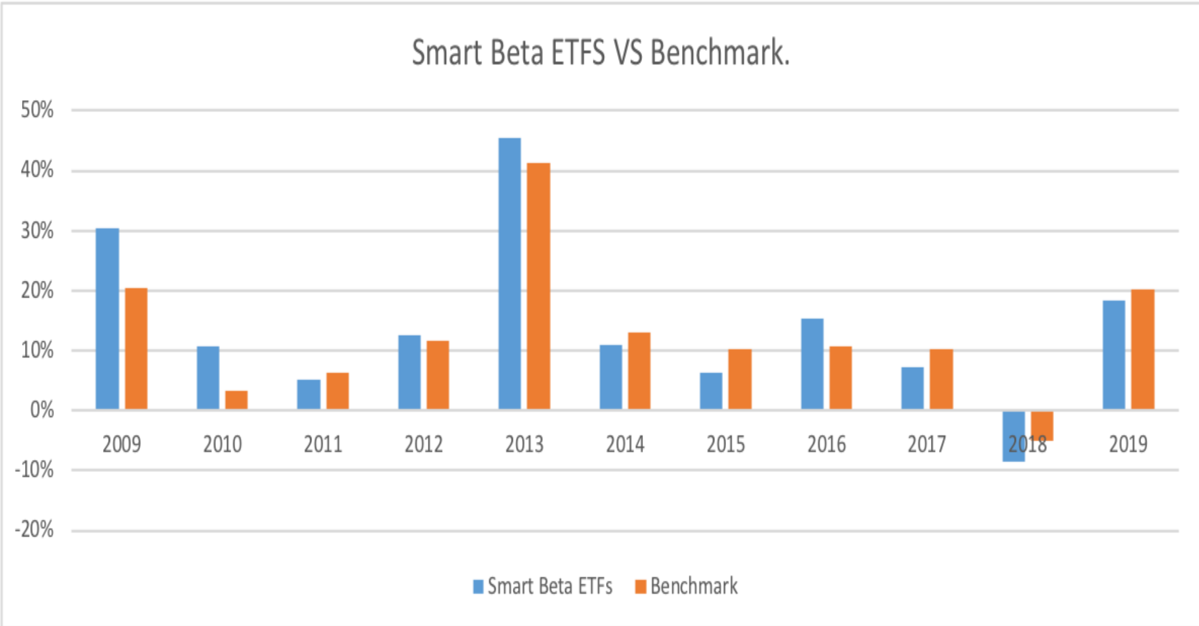

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**Table 1**. Size of Assets Under Management of Smart Beta ETFs

| **Name** | **AUM In U.S. Dollars** |
|---|---|
| Vanguard Growth ETF | 52,040,902,638.96 |
| Vanguard Mid-Cap Growth ETF | 7,500,521,352.13 |
| Invesco S&P 500 Revenue ETF | 1,012,186,154.28 |
| Vanguard Value ETF | 56,707,759,726.46 |
| Invesco S&P MidCap 400 Revenue ETF | 335,894,448.72 |
| Vanguard Small-Cap Growth ETF | 10,400,387,515.39 |
| Invesco S&P SmallCap 600 Revenue ETF | 314,375,787.06 |
| Vanguard Small-Cap Value ETF | 10,400,387,515.39 |
| Invesco Defensive Equity ETF | 314,180,825.86 |
| Total AUM of selected SB ETFs | 143,581,485,716.99 |
| Total AUM of all U.S. SB ETFs | 244,315,044,510.60 |
| Percentage of coverage | 58.8% |

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**Table 2**. Tracking Index of Smart Beta ETFs

| Name | Ticker | Tracking Index |
|---|---|---|
| Vanguard Growth ETF | VUG | S&P 500 Growth Index |
| Vanguard Mid-Cap Growth ETF | VOT | S&P Midcap 400 Growth Index |
| Invesco S&P 500 Revenue ETF | RWL | S&P 500 Revenue-Weighted Index |
| Vanguard Value ETF | VTV | S&P 500 Value Index |
| Invesco S&P MidCap 400 Revenue ETF | RWK | S&P Midcap 400 Revenue-Weighted Index |
| Vanguard Small-Cap Growth ETF | VBK | S&P Smallcap 600 Growth Index |
| Invesco S&P SmallCap 600 Revenue ETF | RWJ | S&P Smallcap 600 Revenue-Weighted Index |
| Vanguard Small-Cap Value ETF | VOE | S&P Smallcap 600 Value Index |
| Invesco Defensive Equity ETF | DEF | S&P 500 |

**Table 3**. Performance Comparison Between Smart Beta ETFs and S&P 500 Benchmark

| | Smart Beta ETFs | | Benchmark S&P 500 |
|---|---|---|---|
| Panel A: 2009–2012 | | | |
| Average Geometric Return (%) | 14.21 | | 10.23 |
| Standard Deviation (%) | 11.05 | | 7.47 |
| Correlation | | 0.97 | |
| Sharpe Ratio | 0.92 | | 0.81 |
| Panel B: 2009–2015 | | | |
| Average Geometric Return (%) | 14.99 | | 14.63 |
| Standard Deviation (%) | 18.57 | | 12.71 |
| Correlation | | 0.94 | |
| Sharpe Ratio | 0.91 | | 0.95 |
| Panel C: 2009–2019 | | | |
| Average Geometric Return (%) | 13.10 | | 12.42 |
| Standard Deviation (%) | 19.51 | | 11.81 |
| Correlation | | 0.92 | |
| Sharpe Ratio | 0.72 | | 0.88 |

Over Various Investment Horizons