

Article

Financial Risk and Better Returns through Smart Beta Exchange-Traded Funds?

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Abstract: Smart beta exchange-traded funds (SB ETFs) have caught the attention of investors due to their supposed ability to offer a better risk–return trade-off than traditionally structured passive indices. Yet, research covering the performance of SB ETFs benchmarked to traditional cap-weighted market indices remains relatively scarce. There is a lack of empirical evidence enforcing this phenomenon. Extending the work of Glushkov (“How Smart are “Smart Beta” ETFs? . . .”, 2016), we provide a quantitative analysis of the performance of 145 EU-domicile SB ETFs over a 12 year period, from 30 December 2005 to 31 December 2017, belonging to 9 sub-categories. We outline which criteria were retained such that the investigated ETFs had at least 12 consecutive monthly returns data. We consider three models: the Sharpe–Lintner capital asset pricing model, the Fama–French three-factor model, and the Carhart four-factor model, discussed in the literature review sections, in order to assess the factor exposure of each fund to market, size, value, and momentum factors, according to the pertinent model. In order to do so, the sample of SB ETFs and benchmarks underwent a series of numerical assessments in order to aim at explaining both performance and risk. The measures chosen are the Annualised Total Return, the Annualised Volatility, the Annualised Sharpe Ratio, and the Annualised Relative Return (ARR). Of the sub-categories that achieved greater ARRs, only two SB categories, equal and momentum, are able to certify better risk-adjusted returns.

Keywords: smart beta; exchange-traded funds; Sharpe–Lintner capital asset pricing model; Fama–French three-factor model; Carhart four-factor model

JEL Classification: G12; G23



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1. Introduction

1.1. Historical Context

Since the roaring 1920s, assets under risk management of global financial corporations have grown exponentially, as has the range of financial products available to investors. In the early 20th century, closed-ended funds (CEFs) were a particularly popular investment vehicle designed to allow investors to collectively pool sums of cash together into one portfolio. CEFs were revolutionary in their ability to provide significant diversification advantages and considerably lower the cost of solo investing (Rouwenhorst 2004). Though proving fatal to its success story, CEFs place restrictions on the redemption of shares, making it difficult for investors to sell out of positions in a timely fashion. Consequently, significant losses were recorded by CEF holders as a result of the Great Depression in the 1930s (Galbraith 1963). This subsequently led to the rise of open-ended funds (OEFs). An OEF allows for the regular creation and redemption of shares. This means that shares of

OEFs can be bought or sold more easily, and thus in times of hardship, investors are able to liquidate their holdings with ease. As a result, ownership of OEFs grew in popularity.

It can be admitted that financial innovation is often a product of financial crisis. Shortly after the financial crash of 1987, the exchange-traded fund (ETF) was developed (Deville 2008; Morningstar 2012). Fundamentally, ETFs and mutual funds (MFs) are analogous. Both products are investment vehicles that invest collective sums of capital in a diversified portfolio of securities based upon a particular underlying investment strategy (Bahadar et al. 2020). An ETF differs from an MF in its ability to be bought and sold on an intraday basis while MFs trade only once a day, typically at market closure. This exchange-traded product (ETP) meets investors' demands for greater market liquidity and enables funds to be traded more flexibly (Vanguard 2016).

With large pools of capital at the hands of the masses of investment professionals, many formulated unique investment styles and strategies to meet the requirements and objectives of their customers. Broadly speaking, these can be categorised as either active or passive strategies. While active fund managers attempt to outperform a given benchmark, the latter simply aim to replicate its performance (Vanguard 2017). Promising higher returns than the market average, active fund managers charge a significant premium for their service relative to their passive counterparts. While there is an ongoing debate residing in the investment community regarding the superiority of active versus passive fund management strategies, the empirical evidence clearly highlights the poor performance record of active fund managers (MSCI 2013; Financial Times 2017). Capital outflows from active funds have escalated due to underperformance and unjust fees. In return, passively managed funds have seen a corresponding rise in capital inflows as a result of their ability to offer superior returns at less of an expense. The net inflow into US-based passively managed funds from active funds is estimated to follow approximately a cubic law (found from data Source: Bloomberg 2017).

Passive instruments such as index funds (e.g., HSBC FTSE 100 Index) aim to fully replicate the performance of a particular market. The fund manager can achieve this by buying all or a sample of the securities in the market or index they seek to track in their respective proportions. Traditionally, this involves weighting the index constituents by market capitalisation, that is, according to total market value of their outstanding shares. This enables the value of the fund to coincide with the changes in the stock prices of its constituents over time.

In recent years, one has seen some considerable growth in the variation and complexity of ETPs (Deloitte 2017). Driven by academic developments in financial theory, the smart beta (SB) ETF is fashioned (Sivaprakash 2015; Krkoska and Schenk-Hoppé 2019). SB is a factor-based approach, not weighted according to a classical market cap, but weighted by factors which are share exposures: size, price, dividend, value growth, momentum, returns, etc. Notice that Wiggins (2018) considers that one could invent strategies based on more than 300 different factors!

SB ETFs represent a more sophisticated range of passively managed financial products that move away from traditional portfolio construction methods by incorporating technicalities of active management (Haakana 2014). Under 'laboratory' conditions, the theory underlying the existence of SB ETFs has proven encouraging in terms of its ability to offer investors optimised risk-adjusted returns relative to traditional index funds (Arnott et al. 2005). However, in reality, there is a lack of evidence to support this case. Therefore, the aim of this paper is to supplement current research, as that of Glushkov (2016) and Thomann and Safoschnik (2019) by providing a European perspective on the performance of SB ETFs.

1.2. Research Questions

In fact, empirical analysis concerning the performance of SB ETFs remains in its infancy. To date, academic studies typically focus on US-domicile equity SB ETFs; this

may be explained by the high concentration of SB products domicile in the region and the availability of data.

Our investigation aims to complement work by [Glushkov \(2016\)](#), “How Smart are “Smart Beta” ETFs? Analysis of Relative Performance and Factor Exposure”, who suggests in fact to extend the analysis to SB ETFs benchmarked against indices outside the USA. Our aim, by considering a sample of EU-domicile SB equity ETFs (as a complementary study to Glushkov on U.S. domiciled domestic equity SB ETFs) is to expand upon past developments and answer the overriding question ‘Do Smart Beta Exchange-Traded Funds Truly Revolutionise Passive Investment Strategies?’. In so doing, we also progress from [Thomann and Safoschnik \(2019\)](#), “Is European Smart Beta smart?”. We intend on answering the question with a particular focus on European SB ETFs: Can EU-domicile SB ETFs generate greater risk-adjusted returns than traditional market capitalisation-weighted indices?

1.3. Paper Overview

After reviewing the key literature principally covering the theoretical framework relevant to this investigation, and pointing out some empirical applications and somewhat still theoretical considerations, but as for practitioners, along portfolio management, we outline the research methodology in a brief section. Thereafter, we provide a comprehensive analysis of the performance of the sample of EU-domicile smart beta ETFs based upon a variety of quantitative assessments. Finally, we deliver concluding remarks regarding the results of this investigation, and touch upon its limitations.

2. Literature Review

This section provides some insight into significant developments in financial risk theory and academic discoveries in chronological order up to the present date, with the aim of providing the basic theoretical framework underpinning theoretical and empirical considerations of SB ETFs. We also point to pertinent applications of such theories or models along portfolio management considerations, with an optimisation perspective, of course.

2.1. Markowitz Modern Portfolio Theory

A theory central to economic and financial academia is [Markowitz \(1952\)](#) Modern Portfolio Theory (MPT). MPT is concerned with the relationship between expected return and risk (as measured by standard deviation) of a portfolio, and theorises how an investor can construct an ‘optimal portfolio’ based on a combination of these components. Markowitz demonstrates how risk-averse investors can alter the constituents of their portfolio in such a way as to maximise the expected return while minimising risk inherent in the portfolio.

Importantly, Markowitz defines the elements of risk that an investor is exposed to: diversifiable and non-diversifiable. Diversifiable or idiosyncratic risk, that is, risk specific to individual securities, is a component of risk that can be eliminated through the process of diversification. In its simplest form, diversification can be explained as a method used by investors to reduce the volatility of returns of a portfolio by allocating capital to a variety of securities, i.e., not placing all of your eggs in one basket. Markowitz expands on this notion of diversification by signifying that it should not solely depend on the number of different securities held within the portfolio, but investors must rather pay considerable attention to the covariance of the returns of the constituents of the portfolio. By pooling securities whose returns do not move in lock-step and possess a correlation coefficient of less than 1, one can significantly reduce the volatility of the returns of the portfolio ([Fisher and Lorie 1970](#)).

Non-diversifiable risk is the element of risk that cannot be eliminated through diversification. Markowitz states, “the returns from securities are too intercorrelated, [thus] diversification cannot eliminate all variance” ([Markowitz 1952](#)). Therefore, providing financial markets are efficient, investors are risk averse and hold well-diversified portfolios, the

portfolio that seemingly offers the highest Sharpe ratio (the average return earned in excess of the risk-free rate per unit of volatility) is the capitalisation-weighted market portfolio.

2.2. The Sharpe–Lintner Capital Asset Pricing Model

Building upon Markowitz MPT, the capital asset pricing model (CAPM) was developed as a product of the combined efforts of [Treyner \(1962\)](#); [Sharpe \(1964\)](#); [Lintner \(1965\)](#) and [Mossin \(1966\)](#). They extended upon the principles of MPT by providing the intuition for non-diversifiable risk, defined in their work as “market risk”. A market risk can be described as the sensitivity of a portfolio to overall market movements, and can be measured by the “market beta” (β_1); the latter “beta”, as for any security, being the ratio of the covariance between the return of the security (R_e) and the return of the market (RM) to the variance of the market returns ([Black 1992](#)):

$$\beta = \text{Covariance}(R_e, RM_t) / \text{Variance}(RM_t).$$

The CAPM offers a more refined understanding of expected return of a portfolio as a function of its risk. It can be formulated as:

$$R_t = RF_t + \beta_1(RM_t - RF_t)$$

where

- R_t : Return on portfolio at time t ,
- RF_t : Return on risk-free interest rate at time t ,
- β_1 : Market beta, and
- RM_t : Return on the market portfolio at time t .

The CAPM equation can also be re-written in terms of the excess return ($R_t - RF_t$) and the risk premium $\beta_1(RM_t - RF_t)$:

$$R_t - RF_t = \beta_1(RM_t - RF_t).$$

Notably, the CAPM prescribes beta as an alternative measure of volatility to standard deviation, as guided by MPT. By considering that the market portfolio has a beta equal to one, a portfolio with a beta coefficient greater than one ($\beta_1 > 1$) assumes higher volatility than the market, while a beta of less than one ($\beta_1 < 1$) assumes lower volatility; a beta of one assumes a portfolio of equal volatility to that of the market. Under the assumption that investors hold well-diversified portfolios, the CAPM considers that the risk premium demanded by investors is proportional to the assumed value of beta, which is the average beta of the securities included in the portfolio ([Brealey et al. 2017](#)).

In summary, the CAPM assumes a linear relationship between the expected return of a portfolio and beta. Therefore, an investor holding a portfolio with a beta above the market portfolio will demand higher returns than the market average. The CAPM advises that holding a portfolio of risky assets is mean-variance optimal ([Sharpe 1964](#); [Lintner 1965](#)). This forms the ideology that a risk-averse investor cannot outperform the market portfolio on a risk-adjusted basis unless additional risk is assumed.

With this in mind, investment professionals have endorsed the use of broad market-cap-weighted stock indices such as the FTSE-All Share Index, the S&P 500 Index, and MSCI World Index as adequate proxies of the CAPM market portfolio. This would also consider such indices as optimal portfolios and thus mean-variance efficient. For a passive investor, the validity of this philosophy by the finance industry eliminates the complexities of optimal portfolio construction and promotes a painless strategy of investing in cap-weighted indices ([Arnott et al. 2005](#)).

However, the composition of the CAPM market portfolio is a topic of controversy. By definition, the market portfolio is a cap-weighted index of all available risky assets, though some critics believe this to be a theoretical concept and impossible to achieve in reality ([Roll 1977](#)). As a result, practitioners have no alternative other than to use proxies

deemed as a sufficient representation of the market. It is argued by Roll (1977) that this empirical failure of the CAPM and the use of proxies, not the true market portfolio, render CAPM application invalid. However, in support of its practical use, Fama and French (2004) argue that as long as the market proxy sits on the minimum variance frontier, it provides a sufficient application in describing the differences in expected returns.

2.3. The Fama–French Three-Factor Model

As with any academic developments, further research highlights a number of pitfalls and empirical failures rejecting the CAPM financial risk model (Shefrin 2002).

The accumulation of research confirms that the positive linear relationship between beta and average return is somewhat flatter than by the CAPM. Initially documented by the likes of Black et al. (1972), and more recently confirmed by Fama and French (1992, 2004). The implication of such a dispute is that the CAPM overestimates expected returns of high-beta stocks and underestimates expected returns of low-beta stocks (Black 1992). Furthermore, experts began to discover market anomalies left unexplained by the CAPM, such as the size effect (Banz 1981) and the value effect (Rosenberg et al. 1985). By ranking firms according to size (the price multiplied by the number of shares outstanding) and book-to-market equity (the ratio of the book value of a common stock to its market value), the authors were able to illustrate these phenomena that contradict the CAPM. Collectively, these factors provide a more comprehensive explanation for the cross-sectional variation in average stock returns and reject the notion of the market beta as a single driver of stock returns as promoted by the CAPM (Fama and French 1993).

The amalgamation of the research sceptical of the CAPM's validity sparked both controversy and innovation. The initial response perceived on Fama and French (1992) proposed that their results could have potentially been arisen due to “data mining”. The existence continuation of certain market anomalies led to the belief that risk could be expressed in a multidimensional form.

Consequently, the empirical contradictions of the CAPM led to the expansion of the single-factor model to include additional risk factors that help to explain the differences in expected returns across stock portfolios that the single market beta cannot. The Fama–French three-factor model builds upon the CAPM to consider multiple factors, the size factor (SMB, “small minus big”) and the value factor (HML, “high minus low”) in addition to the market factor. The size factor aims to capture the risk factor in returns related to market capitalisation (Fama and French 1996). The value factor attempts to capture the risk factor in returns related to book-to-market equity. This factor can be defined as the difference between the returns on portfolios of high and low book-to-market stocks (Fama and French 1996).

The three-factor model can be written as

$$R_t - RF_t = \beta_1(RM_t - RF_t) + \beta_2SMB_t + \beta_3HML_t$$

with notations as before plus

β_2 : Size beta,

SMB_t : Return on small minus big portfolio at time t ,

β_3 : Value beta, and

HML_t : Return on high minus low portfolio at time t .

2.4. The Carhart Four-Factor Model

The revolutionary multifactor model helps to capture a large majority of the cross-sectional variation in expected returns on stock portfolios that the CAPM ultimately fails to deliver (Fama and French 1993). However, as recognised by Fama and French (1996), a shortcoming of this model is its inability to provide an explanation for the momentum effect, as documented by Jegadeesh and Titman (1993). Momentum can be described as the propensity for an upward or downward trend in an asset price to continue over a short

to intermediate time horizon (Jegadeesh and Titman 1993). The three-factor model has since been extended by Carhart (1997) to incorporate momentum (WML—“winner minus loser”), such that

$$R_t - RF_t = \beta_1(RM_t - RF_t) + \beta_2SMB_t + \beta_3HML_t + \beta_4WML_t$$

where in addition to the previous notations, therefore one defines

WML_t : Return on winner minus loser portfolio at time t , and

β_4 : Momentum beta.

2.5. Exploring Cap-Indifferent Indices

Refuting the notion that indices aimed to be representative of the CAPM market portfolio are mean-variance optimal would intuitively suggest the existence of other “more efficient” indices. Likewise, this would support the view that passive investors could in fact do better than to hold what is deemed to be the market portfolio and thus achieve superior risk-adjusted returns (Arnott et al. 2005). Reflecting upon this argument, Arnott et al. (2005) tested a sample of stock market indices whose underlying weighting methodology were based on fundamental factors, or non-market capitalisation measures of firm size, such as book value, revenue, and dividends amongst others as a means of seeking more efficient indices.

Interestingly, over a 43 year observation period, Arnott et al. (2005) revealed that the fundamentals-based portfolios outperformed the S&P 500 Index by 1.97 percentage points per year on average, on a risk-adjusted basis. Therefore, Arnott et al. (2005) evidenced that cap-indifferent indices are more mean-variance efficient than their cap-weighted counterparts. More recently, Arnott et al. (2010) were able to provide evidence to support the superiority of alternative (market-cap-indifferent) weighting methodology over traditional weighting methods as a means of index construction, ultimately forging a new passive investing strategy.

2.6. Smart Beta

The pioneering work of Arnott et al. (2005) led to the conceptualisation of factor-based investing. In the world of finance, a factor can be defined as a macroeconomic, statistical or fundamental characteristic of a financial asset that provides some explanation of their returns and risk (MSCI 2013). For example, the CAPM prescribes the use of the market factor (or market beta). Over the years, researchers have made continuous attempts to uncover other factors that persist throughout time and exist across a range of asset classes. Several have been previously discussed, i.e., size, momentum, and value, as documented by Banz (1981); Jegadeesh and Titman (1993); or Rosenberg et al. (1985). These empirical studies suggest that those factors have exhibited consistent excess returns relative to the market. Such factors are considered as ‘risk premia factors’; this means that they have consistently earned a premium over sustained periods of time “as a result of” exposure to sources of systematic risk (MSCI 2013).

Collectively, factor-based investing and cap-indifferent weighting methodology underpin the relatively new strategy in the investment industry, the so called “smart beta”. Notice that there is no unanimously agreed upon definition of smart beta (SB); thus, it remains an ambiguous term used to describe an “innovative, transparent and low-cost rules-based index construction process” (Morningstar 2014) that “employs alternative weighting and security selection with the goal of outperforming a market-cap-weighted benchmark, reducing portfolio risk, or both” (Mikalachki 2017). In principle, indices or exchange-traded funds (ETFs) formed on the premise of a SB strategy are passive products, which maintain many of the benefits of passive investing (Arnott et al. 2005). However, with the intention to capitalise on factors that are considered to be key drivers of return, SB products also adopt an element of active management. Therefore, SB is often referred to as a hybrid of both active and passive strategies (Financial Times 2017). Nevertheless, “Smart

Beta ETFs may underperform cap-weighted benchmarks and/or increase the portfolio risk.” (Mikalachki 2017).

Thus, the construction of an index encompassing an SB strategy involves utilising alternative weighting methodology or screening method such as dividends, volatility, or quality. This ingenious technique enables the fund manager to actively tilt the portfolio towards particular factors that have shown empirical tendency to provide lower risk or higher returns than traditional indices, or provide a combination of the two. Categorically, SB products can be considered as either return or risk-oriented (Morningstar 2014).

At present, research covering the performance of SB ETFs benchmarked to traditional cap-weighted market indices remains relatively scarce. In 2016, a comprehensive study—“How Smart are “Smart Beta” ETFs?”—was released by Glushkov (2016). With an investigation spanning an 11 year period (2003–2014), Glushkov attempted to document the superior performance of a sample of 164 US-domicile equity SB ETFs relative to their cap-weighted counterparts. Discouragingly, the results of Glushkov’s study provide no definitive evidence that the sample of SB ETFs were able to deliver superior risk-adjusted returns than their benchmarks over the investigation period. Glushkov reported a mediocre 60% of the sampled SB ETFs to deliver superior risk-adjusted returns by outperforming their respective benchmarks, on average, by 1.16% per year. The remainder underperformed their benchmarks by an average of −1.82% per year. Disturbingly, Glushkov documented that the most widely held SB ETF, the dividend-oriented SB ETF, significantly underperformed by an average of −3.90% annually. Therefore, Glushkov (2016) found no clear evidence to support the notion that SB ETFs outperform their risk-adjusted benchmarks in practice. Furthermore, Johnson (2017a, 2017b) held a similar investigation based upon a sample of US-domicile SB ETFs covering a 10 year period ending March 31st 2017. Consistent with Glushkov’s findings, Johnson (2017a, 2017b) also concludes that the sample of SB ETFs offers no definitive improvement upon their cap-weighted counterparts on a risk-adjusted basis. Ropotis (2019) also found that SB ETFs cannot outperform the market, maybe because ETFs move contrary to the growth or decay tendencies of the market. However, Mateus et al. (2020) found that as per the risk-adjusted performance on 152 US equity smart beta ETFs over the period June 2000–May 2017 outperformed their related traditional ETFs, even after expenses. In fact, through a practical argument, di Renzo (2020) considered that one should distinguish active from passive strategies: being flexible might be one (or « the »?) solution for better returns.

2.7. Portfolio Management along Smart Beta Strategies

Within this literature review, in addition to addressing models in order to sustain our study, one should also consider the practical objective of this paper. We can mention a few papers, among a huge literature base, where analyses have been implemented, for portfolio management. As recalled above, theories underlying the existence of SB ETFs have proven encouraging in terms of their ability to offer investors optimised risk-adjusted returns (Arnott et al. 2005). Let us point to Pachamano and Fabozzi (2014)’s review about some widely used approaches to portfolio analytics, discussing traditional and new uses for factor models, investment methodologies of recent interest (such as smart beta).

In fact, a swath of strategies have been designed to provide access to a wide array of return-enhancing risk in the market place for investors and practitioners. Many strategies claim to provide access to the same factors, and one might reasonably expect that they would be similar. However, the ways they are constructed can vary widely. Seemingly small distinctions in index construction can lead to portfolios that have differential drivers of risk and return and unequal exposures to factor and sector biases (Ung and Luk 2016). Ung and Luk review some typical strategies that seek to track common factors (i.e., volatility, momentum, quality, growth, value, dividend yield, and size) in the U.S. market. However, Blitz (2016) stresses that many smart beta strategies do not offer maximum factor exposure but still contain a significant amount of market index exposure as well, or some unexpected exposures to other factors. Yet, the inclusion of the momentum and size factors, and

the selectiveness in stock screening, on the performance and implementation cost of a multifactor strategy, improve the performance and coverage of the multifactor strategy (Chow et al. 2018; Li and Shim 2019).

More globally, since it appears that there is a need for guidance on how to allocate across the ever-increasing array of smart beta products, Dopfel and Lester (2018) developed a framework for investors to blend single-factor and multifactor smart beta within a total portfolio context. Dopfel and Lester (2018) also provided a case study in order to demonstrate how the methodology can be applied to attain better portfolios. In the same line of thoughts, Lee and Kim (2018) provided a review of diverse perspectives from both practitioners and researchers on smart beta strategies. They illustrated their concern by performing empirical and theoretical investigations on the efficiency of smart beta strategies as portfolio management approaches.

Previously, Amenc and Goltz (2007) had outlined the possible uses of ETFs in core satellite portfolio management. With concrete examples, Amenc and Goltz had showed that both the efficient use of ETFs for sub-segments of the bond or equity markets allows investors to create portfolios that beat broad market indices in terms of their risk/return properties, and a dynamic allocation strategy between the core and the satellite portfolio allow investors to gain access to the outperformance of the satellite, while controlling the risk of underperformance.

Thereafter, Kula et al. (2017)'s book digs into every aspect of exchange-traded funds (ETFs) and provides accessible guidance on utilising the indices as part of a productive investment strategy. Very recently, Mateus et al. (2020) analysed smart beta ETF performance of 152 US equity smart beta ETFs over the period June 2000–May 2017 and provided evidence on the funds' performance persistence. They found that the performance of winners and losers does persist in the year ahead.

One cannot end this brief focus on applications without pointing out Maguire et al. (2018) who detailed the construction of a portfolio involving two independent smart beta strategies; the first is a long-short beta-neutral strategy derived from running an adaptive boosting classifier on a suite of momentum indicators, while the second is a minimised volatility portfolio which exploits the observation that low-volatility stocks tend to yield higher risk-adjusted returns than high-volatility stocks. The results reinforce the effectiveness of smart beta strategies, and demonstrate that combining multiple strategies simultaneously can yield better performance than that achieved by any single component in isolation.

3. Methodology

The following section outlines the research methodology of this paper. The content includes a description of the data sample used, how it was collected, and the method of analysis. Let us emphasise that the chosen measures are the Annualised Total Return (ATR), the Annualised Volatility (AV), the Annualised Sharpe Ratio (ASR), and the Annualised Relative Return (ARR), based on 12 months time intervals. We follow a classical route for performing monthly returns-based regression analyses using the CAPM, Fama–French three-factor model and Carhart four-factor model, previously outlined. The mathematical formulae used in the investigation have been presented when outlining the relevant models. It is to be noted that, all data acquired for this paper are in the public domain.

3.1. Data Sample

The data sample produced for the purpose of this investigation was generated using a Bloomberg Terminal. The application of predetermined criteria discussed further below enabled us to create a rather large sample of SB ETFs suitable for this study, 145 SB ETFs, obtained from 7564 at first, through the filters explained here below.

The Bloomberg Terminal contains financial and non-financial information for 7564 primary share class ETFs. First, based on asset class and country of domicile, equity and European Union (EU), respectively, the sample was immediately reduced to 1760 equity

ETFs domicile in the EU. Here, we must point out that there was no restriction placed on the geographic orientation of the markets in which the ETF is benchmarked against or tracks, both domestic and global were included.

Next, by adopting Morningstar's (Morningstar 2014) definition of SB (see Section 2.6 Smart Beta above) and screening criteria as prescribed by their "Strategic Beta Guide", the EU-domicile equity ETFs were categorised in our investigation according to SB attributes, as displayed in Table 1, with emphasis on factors to be discussed below.

Table 1. Smart beta sub-categories; used factors in this study are underlined.

<u>Return Oriented</u>	<u>Risk Oriented</u>	<u>Other</u>
<u>Dividend</u>		
<u>Screened/Weighted *</u>		
<u>Value *</u>		
Size		
Growth		
<u>Fundamentals Weighted *</u>	<u>Low/Minimum</u>	Non-Traditional Commodity
<u>Multifactor *</u>	<u>Volatility/Variance *</u>	Equal Weighted *
Earnings Weighted	Low/High Beta	Non-Traditional Fixed Income
Quality *	Risk Weighted	Multiasset
<u>Expected Returns</u>		
Revenue Weighted		
<u>Momentum *</u>		
<u>Buyback/Shareholder Yield *</u>		

Those that possess a targeted factor exposure or features deemed characteristic of SB, such as dividend screened/weighted, low volatility, and fundamentals weighted, were retained, but the remainders were discarded. Due to data availability (or rather restrictions), those 9 SB that are applicable to this investigation are highlighted with an asterisk (*) and underlined in Table 1. For completeness, it is also important to make the reader aware that in some instances, SB ETFs have been strictly defined as indices that are constructed based upon an alternative index weighting methodology to traditional market capitalisation (Morningstar 2014). However, the comprehensive definition considered by Morningstar is also inclusive of those that have style "tilts", i.e., those with targeted factor exposure or particular characteristics, and subsequently weight the constituents according to their market capitalisation. Therefore, criteria displayed in Table 2 were also applied simultaneously to those of Table 1.

Table 2. Smart beta screening criteria.

<u>Excluded</u>	<u>Included</u>
Market capitalisation-weighted sector indices	
Market capitalisation-weighted country indices	
Thematic indices: for example, clean energy or cloud computing	
Indices that screen constituents strictly on the basis of sector membership or geography	Non-cap-weighted sector indices
Volatility indices	Non-cap-weighted country indices
Indices that employ options strategies	
Indices that underlie products in our "trading" categories, such as leveraged and inverse funds	
Indices that mimic quantitative tactical strategies	

Further amendments were also made to the sample in order to include those cases with an inception date on or before 31 December 2016. This step was made to support a robust investigation by retaining ETFs with at least 12 consecutive monthly returns data.

Finally, only those actively trading were retained for the investigation. This meant a rejection of the ETFs that are no longer trading, dissolved, or were liquidated at any point during the time horizon of this investigation. In fact, Bloomberg Terminal simply does not retain the data for ETFs of these classifications. This ultimately left us with a final sample of 145 SB ETFs, belonging to 9 sub-categories, to be observed within this project (see Tables 1 and 3 and their whole list in Appendix A), their number also depending on the availability year: let us mention the 9 so kept factors with such notations: dividend, low volatility, value, equal, fundamentals, multifactor, quality, momentum, and buyback.

Table 3. Data sample: number of investigated SB ETFs per SB sub-category per year available.

Factor	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Dividend	6	9	9	10	15	15	19	24	27	36	49	53
Low Volatility							3	10	11	13	14	19
Value										3	7	9
Equal						1	3	3	4	10	14	18
Fundamentals			4	7	7	9	9	9	11	11	11	14
Multifactor			1	1	1	1	1	1	1	6	19	21
Quality										1	2	4
Momentum										1	2	4
Buyback											3	3
Total	6	9	14	18	23	26	35	47	54	81	121	145

Each ETF had been directly assigned a benchmark by Morningstar Inc. upon inception, based upon an examination of each ETFs respective prospectus and factsheet. Using this independent source for benchmark allocation mitigates the possibility of a favourable benchmark being chosen by the fund founder for supposed marketing purposes (see Appendix B for the list of benchmarks).

3.2. Method of Analysis

Once we produce this sample of EU-domicile equity SB ETFs and their declared benchmarks, we extract the necessary data for this investigation. The soft data obtained included fund name, ticker, index weighting methodology, SB feature, and inception date. Next, we harvested the historical monthly net asset values (NAVs) of each SB ETF as well as its respective benchmark, and the historical yield of the 10 year German government bund to act as a proxy for the risk-free interest rate. The time horizon chosen for this project is 30 December 2005 to 31 December 2017, mostly due to the lack of available data for the SB ETFs prior to that date.

The sample of SB ETFs and benchmarks underwent a series of numerical assessments in order to aim at explaining both performance and risk. The measures chosen were the Annualised Total Return (ATR), the Annualised Volatility (AV), the Annualised Sharpe Ratio (ASR) and the Annualised Relative Return (ARR)—all of which were calculated based on 12 months time intervals, both since the first year of 12 consecutive monthly returns for SB ETFs and since the corresponding year of the respective benchmarks, going back as far as 30th December 2005. Finally, a monthly returns-based regression analysis was performed using the CAPM, the Fama–French three-factor model and the Carhart four-factor model, as discussed in the literature review sections, to assess the factor exposure of each fund to market, size, value and momentum factors. The data required for each of the factors had been obtained from the Fama–French online data library¹.

3.3. Quantitative Measurements

Table 4 presents which measurements, calculations, and regression models are used in this study.

Table 4. Quantitative measurements and their definition.

Measurement	Definition
Annualised Total Return	Annualised Total Return (ATR) is the geometric average of the return of the fund or benchmark each year over a given time horizon and is a simple measure of absolute performance (Investopedia). As this investigation considers periods of one year, the ATR is calculated by first computing the monthly NAV returns (Rm) of each fund or benchmark and then compounding 12 consecutive monthly returns to reach an annualised figure.
Mathematical Expression	Monthly Return, $Rm_t = \frac{NAV_{t+1} - NAV_{t,0}}{NAV_{t,0}}$
Excel Function	Annualised Total Return, $ATR_t = \text{PRODUCT}(1 + Rm_t:Rm_{t-11}) - 1$
Annualised Volatility	Annualised Volatility (AV) is the standard deviation of the fund returns on an annual basis. It provides a measure of the fluctuation of the funds returns over a given period, and hence how volatile or risky it may be (Morningstar 2014). The AV is calculated as the standard deviation of 12 consecutive monthly returns multiplied by square root of 12.
Excel Function	Annualised Volatility, $\sigma_t = \text{STDEV}(Rm_t:Rm_{t-11}) \times \text{SQRT}(12)$
Annualised Sharpe Ratio	The Sharpe Ratio (Sharpe 1966, 1994) is described as a measure of risk-adjusted performance. The Annualised Sharpe Ratio (ASR) is calculated as the ATR of the fund returns less the annualised risk-free interest rate (RF), over the AV of the fund. In essence, the ASR determines the return per unit of risk endured. When making a comparison between two funds, a higher ASR indicates a superior risk-adjusted performance.
Excel Function	Annualised Sharpe Ratio, $ASR_t = \frac{ATR_t - RF_t}{\sigma_t}$
Annualised Relative Return	Annualised Relative Return (ARR) is defined as the excess return of the SB ETF relative to a specified benchmark. The ARR is calculated as the difference between the ATR of the SB ETF and the ATR of its benchmark.
Excel Function	Annualised Relative Return, $ARR_t = ATR_{SB\ ETF,t} - ATR_{BM,t}$ where <ul style="list-style-type: none"> - $ATR_{ETF,t}$: ATR of a SB ETF at time t - $ATR_{BM,t}$: ATR of the prescribed benchmark at time t
CAPM	$Rm_{SB\ ETF,t} - RF_t = \alpha_t + \beta_1(Rm_{BM,t} - RF_t) + \varepsilon_t$ where <ul style="list-style-type: none"> - $Rm_{SB\ ETF,t}$: Monthly absolute return of a SB ETF at time t - RF_t: Risk-free interest rate at time t - α_t: Alpha at time t - β_1: Market beta - $Rm_{BM,t}$: Monthly absolute return of a benchmark at time t - ε_t: Error term
Three-Factor Model	$Rm_{SB\ ETF,t} - RF_t = \alpha_t + \beta_1(Rm_{BM,t} - RF_t) + \beta_2SMB_t + \beta_3HML_t + \varepsilon_t$ where <ul style="list-style-type: none"> - β_2: Size beta - SMB_t: Return on small minus big portfolio at time t - β_3: Value beta - HML_t: Return on high minus low portfolio at time t
Four-Factor Model	$Rm_{SB\ ETF,t} - RF_t = \alpha_t + \beta_1(Rm_{BM,t} - RF_t) + \beta_2SMB_t + \beta_3HML_t + \beta_4WML_t + \varepsilon_t$ where <ul style="list-style-type: none"> - WML_t: Return on winner minus loser portfolio at time t - β_4: Momentum beta

4. Analysis of Results

This section contains a descriptive analysis of the empirical results generated from the quantitative metrics discussed in Sections 3.2 and 3.3, starting with the Annualised Relative Return (ARR), the Annualised Volatility (AV), the Annualised Sharpe Ratio (ASR), and the regression analysis performed using the CAPM, the three-factor model, and the four-factor model.

For most of this section, we have decided to focus the analysis on either dividend-oriented SB ETFs or fundamentals-weighted SB ETFs, due to the data best availability, and appropriate meaning.

4.1. The Annualised Relative Return (ARR)

From a marketing perspective, SB ETFs have been largely sold upon their ‘ability’ to achieve returns greater than traditional cap-weighted indices. The Annualised Relative Return (ARR) quantifies the difference between the Annualised Total Return (ATR) of the SB ETF and the ATR of the corresponding benchmark, hence providing an indication of outperformance (highlighted in bold face) or underperformance. Tables 5 and 6 provide the results of either the dividend or the fundamentals-weighted SB ETFs, respectively, over time; both ATRs and ARRs have been averaged across each annual period and thus incorporate the respective figures for each SB ETF and benchmark actively trading in that year (see Table 3 for the information on respective years).

Table 5. Average ARR of dividend-oriented SB ETFs versus respective benchmarks.

Date	SB ETF ATR		Benchmark ATR		ARR	
	Average	Median	Average	Median	Average	Median
2006	21%	21%	22%	22%	−1%	+3%
2007	−1%	−2%	9%	8%	−10%	−12%
2008	−50%	−48%	−41%	−42%	−9%	−12%
2009	29%	27%	30%	27%	−2%	−0%
2010	8%	6%	9%	11%	−1%	−2%
2011	−11%	−13%	−9%	−15%	−2%	−2%
2012	8%	6%	18%	18%	−10%	−11%
2013	13%	15%	21%	23%	−8%	−10%
2014	5%	4%	2%	2%	+2%	+2%
2015	−2%	0%	1%	−2%	−2%	−2%
2016	11%	7%	8%	7%	+4%	+1%
2017	6%	7%	17%	16%	−11%	−9%

Table 6. Average ARR of fundamentals-weighted SB ETFs versus respective benchmarks.

Date	SB ETF ATR		Benchmark ATR		ARR	
	Average	Median	Average	Median	Average	Median
2008	−31%	−33%	−45%	−45%	+14%	+16%
2009	30%	26%	40%	34%	−10%	−6%
2010	15%	18%	11%	11%	+4%	+4%
2011	−14%	−16%	−10%	−10%	−4%	−3%
2012	13%	10%	15%	15%	−3%	−1%
2013	17%	17%	18%	20%	−1%	−2%
2014	6%	7%	2%	2%	+4%	+5%
2015	−1%	0%	−3%	−3%	+2%	+0%
2016	23%	20%	7%	6%	+17%	+12%
2017	12%	10%	17%	20%	−5%	−7%

By first considering Table 5, one observes that the average ARR of the dividend-oriented SB ETFs provides a clear evidence of a continuing poor performance relative to their benchmarks indices over the years. As can be seen also from Table 5, the maximum

positive average ARR is +4% in 2016, while the maximum negative average ARR is −11% in 2017. Thus, dividend-oriented SB ETFs failed to outperform their benchmarks on average, in 10 out of the 12 years here studied. For more information, notice that amongst this SB category, the maximum annualised outperformance recorded was +36% achieved by WisdomTree Emerging Markets SmallCap Dividend UCITS ETF in 2016 versus an average of +4% and a median of +1%. In contrast, the maximum annualised underperformance recorded was −34% by iShares Dow Jones Asia Pacific Select Dividend 3 UCITS DE in 2017 versus an average of −11% and median of −9%.

Next, consider Table 6. In comparison to the dividend-oriented SB ETFs, the fundamentals-weighted SB ETFs signal outperforms on 50% of the years considered versus 17% for dividend-oriented SB ETFs. However, over the time period here considered, 50% of cases also present years of underperformance. From a glance, it can be admitted that fundamentals-weighted SB ETFs provide greater returns than dividend-oriented SB ETFs when considering similar time periods. In 2016, fundamentals-weighted SB ETFs provide an ARR of +17% versus +4% dividend-oriented SB ETFs, and only −5% versus −11% in 2016.

However, there is no conclusive evidence to suggest that either category of SB ETFs predictably provide greater returns than their cap-weighted benchmarks. Table 7 provides an overview of the average ARR for each SB category over time. Table 7 evidences that 5 of the 9 SB categories were successful in achieving an average ARR greater than their benchmarks in more than 50% of the observation periods.

Table 7. Average ARR for each SB category over the investigated time interval.

Date	Dividend	Low Volatility	Value	Equal	Fundamentals	Multifactor	Quality	Momentum	Buyback
2006	−1%	-	-	-	-	-	-	-	-
2007	−10%	-	-	-	-	-	-	-	-
2008	−9%	-	-	-	+14%	+19%	-	-	-
2009	−2%	-	-	-	−10%	−16%	-	-	-
2010	−1%	-	-	-	+4%	+3%	-	-	-
2011	−2%	-	-	+24%	−4%	−8%	-	-	-
2012	−10%	−6%	-	−26%	−3%	−6%	-	-	-
2013	−8%	−3%	-	−26%	−1%	+6%	-	-	-
2014	+2%	+6%	-	+7%	+4%	+3%	-	-	-
2015	−2%	+5%	+9%	+4%	+2%	+4%	+3%	+4%	-
2016	+4%	−4%	+2%	+7%	+17%	+4%	−3%	−3%	−2%
2017	−11%	−6%	−2%	−8%	−5%	−4%	+2%	+10%	−5%

4.2. The Annualised Volatility (AV)

The next step of the investigation involved testing the volatility of returns of the SB ETFs—as measured by standard deviation. The Annualised Volatility (AV) is calculated as the annualised standard deviation of the returns of the SB ETF and the corresponding benchmark. The AV hence provides a measure of dispersion of the returns of the SB ETF or benchmark from the mean value of returns across rolling windows of 12 months. Figures 1 and 2 provide a graphical representation of the results of the dividend-oriented and fundamentals-weighted SB ETFs, to which we add low volatility-weighted SB ETFs, respectively, over time (Figure 3). The AVs have then been averaged across each annual period to incorporate the respective figures for each SB ETF and benchmark actively trading in that year; see Table 3 for recalling the years.

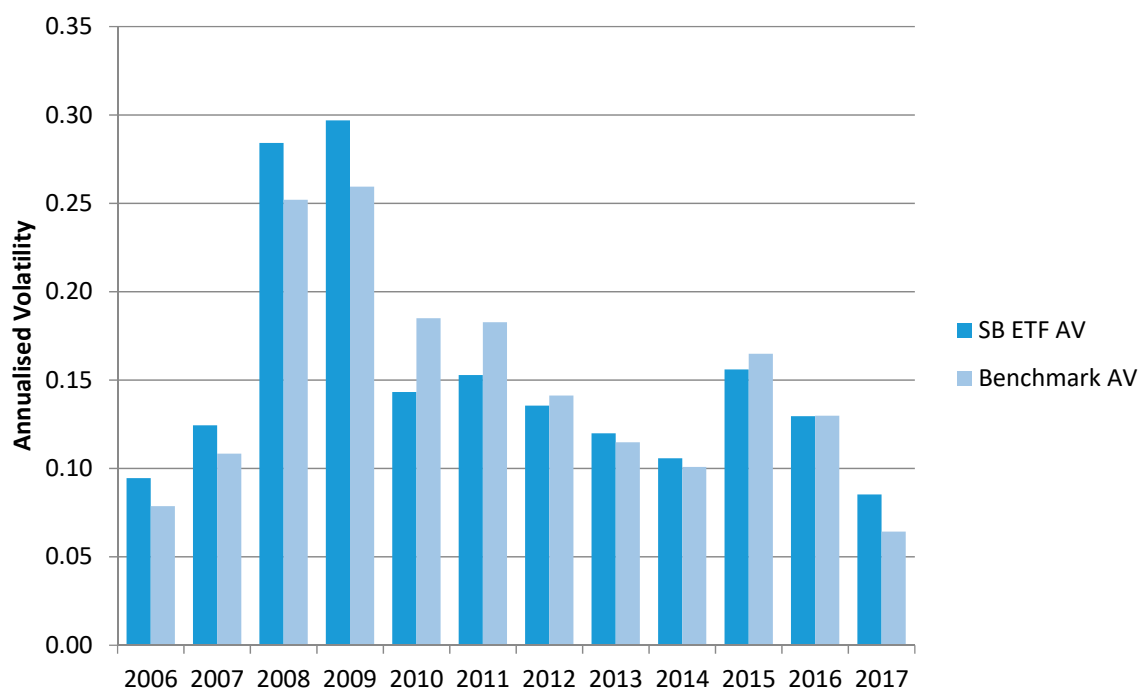


Figure 1. Average AV of dividend-oriented SB ETFs versus respective benchmarks.

It is evident to see in all three cases that there are not many notable differences in volatility of returns across the time horizons studied. Figure 1 shows that in 2010, the dividend-oriented SB ETFs experience a volatility of 0.04 less than their benchmarks; the maximum recorded positive difference in the average AV. On the contrary, the fundamentals weighted SB ETFs (Figure 2) experienced an average AV of 0.30 versus the benchmarks 0.26 in 2009, thus 0.04 more volatile; the maximum negative difference in the average AV. More generally, or 60% of the time, the dividend-oriented SB ETFs experience a higher average volatility than their respective benchmarks.

Figure 3 provides a graphical representation of the AV of returns of the low volatility-weighted SB ETFs. Low volatility SB ETFs are categorised as a risk-oriented strategy by Morningstar (2012). Recall that this SB category weights their constituents based on historical volatility and, as the name implies, objectively intends to reduce volatility (or risk) while maintaining or enhancing returns. Interestingly, on average, 67% of the low volatility SB category exhibits a lower AV of returns than their corresponding benchmarks. However, the difference is negligible, in the years in which the low volatility SB ETFs reflect a higher volatility than their benchmarks.

In summary, it can be said that low volatility-weighted SB ETFs certainly provide lower risk relative to their benchmark indices and thus meet its objective. However, as seen in the other cases there is no clear evidence to suggest that either category of SB ETFs provide lower volatility of returns than their cap-weighted benchmarks. Overall, three out of nine SB categories exhibit lower volatilities than their benchmarks more often than not, while six out of nine SB categories experience higher volatility than their benchmarks (see Appendix C for the complete results).

With reference to Figure 2, in the year 2011, the fundamentals-weighted SB ETFs exhibited a volatility of 0.15 versus the benchmarks 0.20. The difference of 0.05 was the maximum recorded difference in volatility across the study period (2008–2017). However, in 2009 the fundamentals-weighted SB ETFs also experienced a period of higher volatility than their prescribed benchmarks, 0.30 versus 0.27, respectively. In summary, out of 5 of the 10 years studied the fundamentals-weighted SB ETFs experienced a higher average volatility than their respective benchmarks, and vice versa, therefore ensuring lower volatility of returns than the dividend-oriented SB ETFs. Notably in both cases, in times of abnormally high market volatility (see illustration through VIX display, Figure A1, in

Appendix D), i.e., 2009 during the financial crash 2010 flash crash, 2011 European sovereign debt crisis, SB ETFs experience the biggest differences in volatility, both positive and negative.

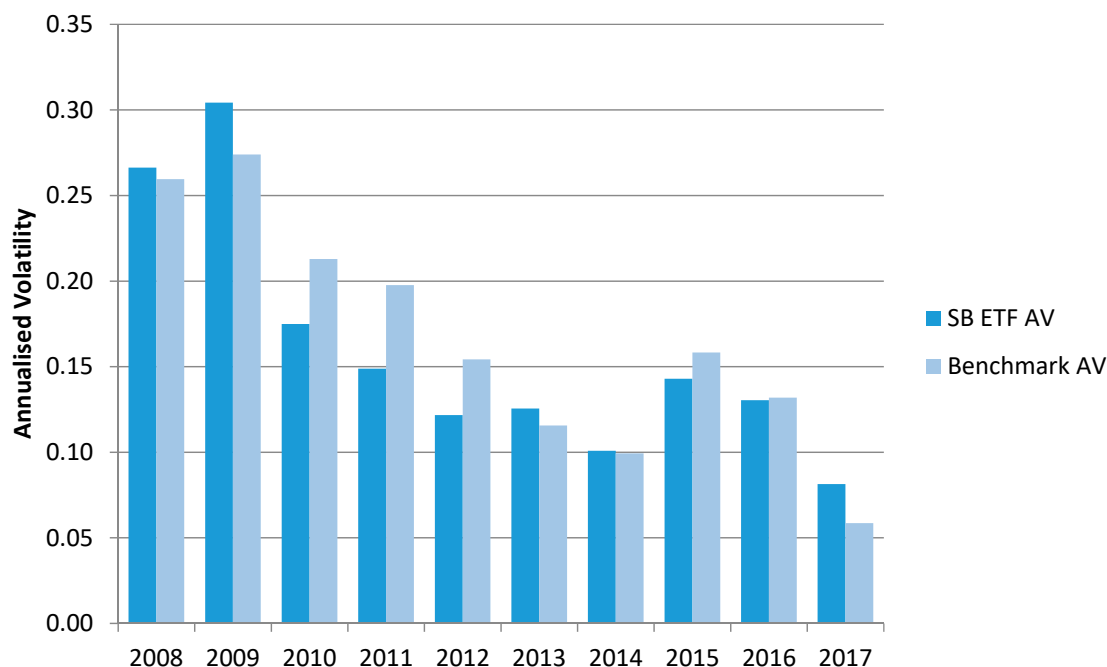


Figure 2. Average AV of fundamentals-weighted SB ETFs versus respective benchmarks.

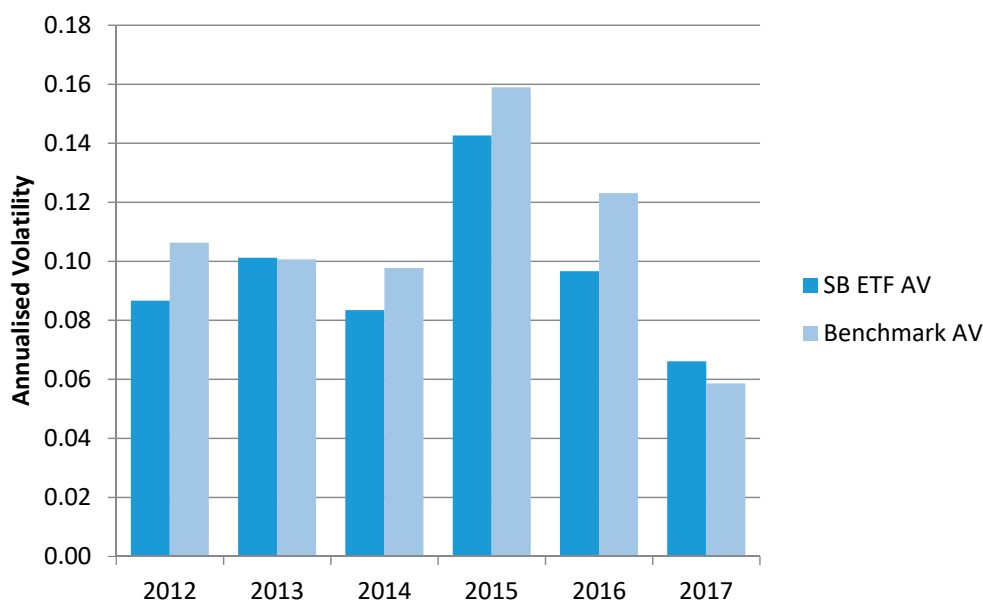


Figure 3. Average AV of low volatility-weighted SB ETFs versus respective benchmarks.

4.3. The Annualised Sharpe Ratio (ASR)

After calculating both the ATRs and AVs of each SB ETF and the respective benchmarks, we can compute the Annualised Sharpe Ratio (ASR). The risk-free interest rate used in this process was an annualised version of the 10 year German government bund (sourced from Bloomberg). As previously mentioned, the ASR provides a measure of risk-adjusted returns, and hence the amount of returns achieved per unit of risk. An $ASR < 1$ shows that the returns on the SB ETF or benchmark are less than the risk taken, while an $ASR > 1$ signals that the returns achieved are greater per unit of risk; an $ASR = 1$

indicates that the returns generated are proportional to the risk endured. Additionally, a negative ASR suggests that either the SB ETF or benchmark generate returns less than the risk-free interest rate. SB ETFs pride themselves on offering greater risk-adjusted returns than traditional cap-weighted indices; hence, we would expect to see better risk-adjusted results from the sample than the passive benchmarks. Again, we decided to use a bold face to signal those SB ETFs providing higher risk-adjusted returns relative to their benchmarks and a red highlighter to signal lesser risk-adjusted returns relative to their benchmarks. Each ASR is calculated with rolling windows of 12 months since inception for each SB ETF and since the corresponding year of the respective benchmarks. Averages were then taken across each yearly period to express the results for each SB ETF and benchmark actively trading in that year (see Table 3 for the year details).

Tables 8 and 9 provide an example of the results of the dividend-oriented and fundamentals-weighted SB ETFs, respectively, over time. The yearly better performances are emphasised.

Table 8. Average ASR of dividend-oriented SB ETFs and the respective benchmarks; better performance is highlighted in bold faced.

Date	SB ETF ASR		Benchmark ASR	
	Average	Median	Average	Median
2006	1.81	2.02	2.43	1.98
2007	−0.51	−0.48	0.42	0.35
2008	−1.94	−1.99	−1.78	−1.84
2009	0.85	0.88	1.06	1.05
2010	0.46	0.20	0.37	0.46
2011	−0.81	−1.00	−0.62	−0.67
2012	0.44	0.41	1.18	1.29
2013	1.03	1.03	1.69	1.84
2014	0.52	0.29	0.18	0.14
2015	−0.13	−0.06	−0.02	−0.15
2016	0.81	0.53	0.64	0.39
2017	0.80	0.68	2.89	2.34

Table 9. Average ASR of fundamentals-weighted SB ETFs and the respective benchmarks; better performance is highlighted in bold faced.

Date	SB ETF ASR		Benchmark ASR	
	Average	Median	Average	Median
2008	− 1.35	−1.22	−1.90	−1.88
2009	0.88	0.78	1.37	1.32
2010	0.73	0.76	0.38	0.45
2011	−1.11	−1.25	−0.62	−0.61
2012	0.96	0.83	1.01	0.90
2013	1.27	1.46	1.65	1.77
2014	0.58	0.77	0.00	−0.49
2015	− 0.05	−0.09	−0.29	−0.33
2016	1.81	1.59	0.51	0.45
2017	1.58	1.27	3.55	3.33

Table 8 shows that in 2014, the dividend-oriented SB ETFs generate a maximum outperformance relative to their benchmarks of 0.35, on average. In 2017, the dividend-oriented SB ETFs not only achieve an ASR < 1, but underperform their benchmarks on average by 2.09, a significantly large underperformance (see Table 10). In summary, the dividend-oriented SB ETFs fail to outperform their cap-weighted benchmarks on a risk-adjusted basis in 9 of the 12 years studied.

With reference to Table 9, in 2016 fundamentals-weighted SB ETFs achieved an average ASR of 1.81 versus the benchmarks 0.51; also a relative outperformance of 1.30 (see Table 10).

On the other hand, in 2017 the SB ETFs also underperformed their benchmarks on average by 1.97. Therefore, the fundamentals-weighted SB ETFs generated greater risk-adjusted returns than their benchmarks 50% of the years studied, while underperforming the remainder. Consistent with the previous performance indicators, we can conclude that fundamentals-weighted SB ETFs provide greater risk-adjusted returns than dividend-oriented SB ETFs. However, the overall results do not provide sufficiently convincing evidence to suggest that fundamentals-weighted SB ETFs can consistently outperform their benchmarks.

Table 10 provides the complete overview of the difference between the average ASR of each SB category and their benchmarks over time. Disappointingly, alas, it is clear to see that only 2 out of 9 SB categories are able to provide superior risk-adjusted returns than their benchmarks over 50% of the periods studied. Of the five categories that achieved greater ARRs, only two SB categories, equal and momentum, are able to certify better risk-adjusted returns.

Table 10. Summary of the average ASR for each SB category relative to their respective benchmarks over time; best performances are highlighted in bold faced.

Date	Dividend	Low Volatility	Value	Equal	Fundamentals	Multifactor	Quality	Momentum	Buyback
2006	−0.62	-	-	-	-	-	-	-	-
2007	−0.93	-	-	-	-	-	-	-	-
2008	−0.17	-	-	-	0.55	0.88	-	-	-
2009	−0.22	-	-	-	−0.49	−0.64	-	-	-
2010	0.09	-	-	-	0.35	0.29	-	-	-
2011	−0.19	-	-	0.11	−0.49	−0.41	-	-	-
2012	−0.74	−0.35	-	−0.75	−0.05	−0.30	-	-	-
2013	−0.66	−0.41	-	−0.72	−0.38	−1.52	-	-	-
2014	0.34	0.99	-	0.89	0.59	0.05	-	-	-
2015	−0.10	0.28	0.52	0.34	0.24	0.31	0.23	0.33	-
2016	0.17	−0.28	−0.01	0.02	1.30	0.30	−0.34	−0.15	−0.12
2017	−2.09	−1.47	−1.10	−1.64	−1.97	−1.49	−0.89	0.12	−2.28

4.4. Regression Analysis

This section contains the results of the regression analysis carried out using the CAPM, the three-factor model and the four-factor model. The regression analysis highlights each SB ETFs exposure to particular risk premia and helps to identify whether they have successfully taken advantage of particular factors as strategically intended. In order to perform a monthly returns-based regression analysis, we require five key items: the factor model, SB ETF monthly returns data, benchmark monthly returns data, monthly risk-free interest rate, and monthly returns data of the size, value and momentum factors.

Once one gathers all of these relevant data, one can perform a monthly returns-based regression for each SB ETF since its inception. We report such an average, and the median, across those particular variables to construct a consolidated summary output per SB category, in Table 11, for the CAMP, and in Tables A1 and A2, in Appendices E and F for the two other models.

4.4.1. The CAPM

The first regression analysis was conducted using the single-factor model, the CAPM. Table 11 provides the regression summary outputs of the CAPM regression analysis by taking averages of key variables previously mentioned.

As can be seen from Table 11, 4 averages of the 9 SB categories, value, fundamentals, quality, and buyback, display an R-square equal to or above 70%, thus exhibiting a good correlation within this CAPM. The remaining 5 categories display an R-square between 40 and 70% and thus reveal an average correlation with the CAPM. For example, the results show that dividend-oriented SB ETFs have an R-square of 59%, and hence 59% of movements in the SB ETF can be explained by movements in the CAPM, versus fundamentals-weighted

SB ETFs with an R-square of 70%, which suggests 70% of movements in these SB ETFs can be explained by the CAPM. In terms of significant F, all values are ≤ 0.05 . This suggests that all of the results did not occur by chance.

Table 11. Consolidated single-factor (CAPM) regression summary output.

Factor		R ²	Signif. F	Alpha $\times 10^3$	p-Value	Market Beta $\times 10^3$	p-Value
Dividend	Average	59%	5.4425×10^{-2}	−2.5073	0.40200	0.76831	5.4425×10^{-2}
	Median	65%	4.9376×10^{-14}	−2.0656	0.33695	0.86109	4.9376×10^{-14}
Low Volatility	Average	68%	1.3572×10^{-3}	−1.3367	0.48181	0.77383	1.3572×10^{-3}
	Median	74%	6.6007×10^{-13}	−0.3914	0.50615	0.76988	6.6007×10^{-13}
Value	Average	77%	3.3920×10^{-6}	0.3216	0.39178	1.11720	3.3920×10^{-6}
	Median	84%	1.2000×10^{-8}	0.3290	0.25519	1.04040	1.2000×10^{-8}
Equal	Average	60%	2.1809×10^{-2}	−1.6266	0.45101	0.87565	2.1809×10^{-2}
	Median	57%	2.8740×10^{-6}	−1.1959	0.44041	0.91573	2.8740×10^{-6}
Fundamentals	Average	70%	2.0000×10^{-7}	−0.4324	0.50792	0.87367	2.0000×10^{-7}
	Median	76%	1.1624×10^{-24}	−0.4060	0.48797	0.81113	1.1624×10^{-24}
Multi—Factor	Average	61%	4.9362×10^{-2}	2.0413	0.48525	0.75180	4.9362×10^{-2}
	Median	83%	4.0647×10^{-11}	0.6536	0.51467	0.81153	4.0647×10^{-11}
Quality	Average	89%	1.9310×10^{-6}	−1.5455	0.52674	1.03810	1.9310×10^{-6}
	Median	89%	2.5000×10^{-8}	−1.2821	0.51401	0.98164	2.5000×10^{-8}
Momentum	Average	63%	2.4992×10^{-2}	4.1446	0.36675	0.80678	2.4992×10^{-2}
	Median	72%	2.0207×10^{-4}	3.0030	0.36774	0.84088	2.0207×10^{-4}
Buyback	Average	75%	1.3100×10^{-7}	−2.1195	0.38517	1.16660	1.3100×10^{-7}
	Median	80%	7.3323×10^{-13}	−3.2950	0.39883	1.22030	7.3323×10^{-13}

Recall that an alpha is considered to be a measure of the difference between the SB ETFs actual returns and its expected performance, given its level of risk as measured by a beta. An alpha is typically used as a measure of performance of active fund managers. As SB ETFs are passive instruments, alpha is expected to be close to or equal to zero. Interestingly, alpha is negative in most cases, thus except for value, multifactor, and momentum, thereby suggesting that the ETF has underperformed the benchmark given its level of risk. In other cases, alpha has been recorded, but is negligible as anticipated. However, reflecting on the P-values for each alpha would suggest that most results are due to complete randomness (all values are ≥ 0.05).

The final step of this regression analysis involved studying the market beta of each SB ETF category. Generally speaking, passive instruments seek to mimic the movements of a broader benchmark. That being said, the market beta of passive instruments should be equal to 1 to replicate that of the market. Table 11 shows that 6 out of 9 SB categories have a market beta of less than or close to 1, while the remainder have a market beta ≥ 1 . The p-value also confirms that these results did not occur by chance as each value is ≤ 0.05 .

4.4.2. The Three-Factor Model

The next regression analysis was performed using the Fama–French three-factor model which incorporates the size factor and the value factor along with the market factor. As can be seen from Table A1 (Appendix E), 6 of the 9 SB categories display an R-square of above 70% exhibiting a good correlation with the three-factor model; this is a marginal increase from what is seen in the CAPM regression analysis. The remaining 4 categories display an R-square between 40 and 70% and thus reveal some auto-correlation within this three-factor model. Using the same examples, the dividend-oriented SB ETFs and fundamentals-weighted SB ETFs, the results show an R-square of 65% and R-square of 74%, respectively. The significant F values remain ≤ 0.05 , while the generated alpha remains

close to zero or “increase further negatively”. However, reflecting on the p -values again for each alpha shows that most results suggest a completely random process (≥ 0.05).

Appendix E (Table A1) shows that the market beta remains at similar levels (≤ 1), albeit increased slightly, from what can be seen in Table 11, the CAPM regression analysis. The p -value also confirms that these results did not occur by chance as each value is ≤ 0.05 , other than the multifactor model.

From these results, it can be concluded that the large majority of SB ETFs show no exposure towards the size factor or value factor as most of the values computed are negative. Of those that are positive, the P -values shown are (≥ 0.05) and thus have likely to have occurred due to randomness. Interestingly, the value-weighted SB ETFs show a positive beta coefficient, but again, the p -value confirms its likely random occurrence.

4.4.3. The Four-Factor Model

As can be seen from Table A2 in Appendix F, 7 of the 9 SB categories now display an R-square of above 70% exhibiting a good correlation with the four-factor model. The remaining 2 categories, dividend-oriented SB ETFs and equal-weighted, display an R-square between 40 and 70%, close to 70%, and thus reveal an average correlation with the four-factor model. Significance F and alpha remain almost unchanged.

Finally, it is of interest to analyse the exposure to the market beta, size, value and momentum factor of each SB ETF category. Displayed values in Appendix F show that almost all of the SB categories exhibit a negative exposure to these additional three factors while the market beta coefficient has increased marginally. The p -values also confirm that these results likely occurred by chance as each value is significantly greater than 0.05, with the exception of the momentum-oriented SB ETFs which exhibit a momentum beta of 0.005 and a p -value ≤ 0.05 .

5. Conclusions

5.1. Recalling Research Questions

To conclude, let us begin by restating the questions of this investigation and follow each with a summary of the findings.

- (1) Can EU-domicile SB ETFs generate greater risk-adjusted returns than traditional market capitalisation-weighted indices?

According to the ARRs computed, as reported in Table 7, five of the nine SB categories can be considered to have been able to achieve greater returns than their benchmarks over the time horizon studied. However, once some risk is taken into account, it is easy to see that SB ETFs fail to outperform their benchmarks on average. This is largely as a result of a combination of low levels of returns as well as a higher volatility relative to their cap-weighted counterparts. These results allow us to conclude that cap-weighted indices would have been a better investment than the SB ETFs studied when considering risk and achieved returns.

- (2) Do Smart Beta Exchange-Traded Funds Truly Revolutionise Passive Investment Strategies?

To provide an answer to this crucial question, one can say, based upon the selection of data acquired and subsequently analysed, that the sample of EU-domicile SB ETFs here studied does not seem to enhance the capabilities of traditional cap-weighted investment products by tilting the index towards particular factors in attempt to harvest risk premiums, in brief, therefore not providing a superior performance. In light of this, we have to suggest that investors should keep holding funds in traditional cap-weighted indices to achieve broad diversification and greater returns than for both actively managed ETFs and active-passive hybrids of the SB sort.

In fine, these answers extend the findings of Glushkov (2016) and the conclusions in the thesis of Thomann and Safoschnik (2019) because our quantitative analysis is based on

the performance of 145 EU-domicile SB ETFs, belonging to 9 sub-categories, over a long (and rather recent) lapse of time, 12 years.

5.2. Limitations of Analysis and Suggested Further Research

Even though we conclude with a significant answer to three crucial questions, it is fair to admit that there are limitations to the present analysis. A brief note follows:

First of all (as pointed out by a reviewer who we thereby acknowledge for insisting that we mention the point) not all examined ETFs have been built in order to consider the hereby examined factors. For examples, the suite of BMO MSCI Income Leaders ETFs were (are) built combining two factors: quality and yield strategies. Yet, we do not use quality and yield as the only pertinent factors to assess whether such ETFs effectively capture intended factor-risk premiums, since we insist on market, size, value, and momentum only. In order to coherently assess whether the intended factor-risk premiums are effectively capturing the intended factor-risk premiums, one might have to reconsider each ETFs with respect to the truly intended factor-risk premiums on which the SB ETF strategies were (are) actually built. In such a sense, one could avoid reaching a misleading conclusion, resulting from a deduction based on a non-actively pursued strategy.

5.2.1. Lack of Data

Most of the sample SB ETFs have an inception date within the last 5 years. As a consequence, much of the calculations could be skewed by an inadequate data set. As usual, a continuous examination of the market is a relevant suggestion. Error bars are always indicative of risk and inherent reliability of risk management.

5.2.2. Inconsistent Time Intervals

In addition, we find it difficult to provide a comparison of the performance between SB categories over time due to an inconsistency in the availability of data for each SB ETF relative to another. Should this not have been the case, it would have allowed us to make an even better comparison of the effectiveness of each SB category relative to another over the same time period. However, with such a variance in the amount of observable data for each SB ETF and SB category as a whole, a performance comparison between two SB categories over time is not realistically possible.

5.2.3. Survivorship Bias

It was impossible to remove survivorship bias from the sample chosen by including inactive ETFs.

5.2.4. Exchange Rate

Recently, it was asked whether exchange-traded funds are influenced by exchange rate fluctuations. Currency exchange rate fluctuations impact stock markets, and are expected to influence the sensitivity of ETFs. In a recent study, [Geetha et al. \(2020\)](#) utilise the currency rate data from 2013 to 2018 of USD, GBP, and INR and examine its effect on the NDX (NASDAQ). The study emphasises that the ETF as a basket of securities is insensitive to currency rate fluctuations. [Geetha et al. \(2020\)](#) found that the response of the ETF to the currency movements is likely due to its underlying index. The study concludes that there is no direct impact between ETF and index performance through exchange rate fluctuations.

5.2.5. Further Perspective

The next generation of investigations is the five-factor model ([Fama and French 2015](#)). The five-factor model incorporates profitability and investment patterns to size and book-to-market equity ratio factors in addition to the market factor. It has been expressed that the five-factor model performs better than the Fama–French three-factor model or the Carhart four-factor model in explaining the cross-section of average stock returns ([Artmann et al. 2012](#)). [Blitz \(2012\)](#) argued for allocating strategically to value, momentum,

and low volatility equity factor portfolios, and also found some added value for these two new factors in Fama and French (2015)'s five-factor model (Blitz 2015).

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Informed Consent Statement: Not applicable.

Data Availability Statement: The data sample produced for the purpose of this investigation was generated using a Bloomberg Terminal; <https://www.bloomberg.com/europe>.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. List of All Studied SB ETFs per SB Sub-Category

Dividend (53 Cases)
PowerShares FTSE UK High Dividend Low Volatility UCITS ETF
PowerShares FTSE Emerging Markets High Dividend Low Volatility UCITS ETF
THINK Morningstar High Dividend UCITS ETF
First Trust US Equity Income UCITS ETF
ComStage 1 DivDAX UCITS ETF
WisdomTree Emerging Asia Equity Income UCITS ETF
WisdomTree UK Equity Income UCITS ETF
AMUNDI ETF MSCI Europe High Dividend Factor UCITS ETF—D
AMUNDI ETF MSCI EMU HIGH DIVIDEND UCITS ETF—D
Deka EURO iSTOXX ex Fin Dividend + UCITS ETF
First Trust Global Equity Income UCITS ETF
LYXOR SG Global Quality Income NTR UCITS ETF—Monthly Hedged C-GBP
PowerShares S&P 500 VEQTOR UCITS ETF
WisdomTree Japan Equity UCITS ETF—USD Hedged
WisdomTree Europe Equity UCITS ETF—USD Hedged
WisdomTree Germany Equity UCITS ETF—GBP Hedged
PowerShares S&P 500 High Dividend Low Volatility UCITS ETF
WisdomTree Emerging Markets Equity Income UCITS ETF
WisdomTree Emerging Markets SmallCap Dividend UCITS ETF
WisdomTree Europe SmallCap Dividend UCITS ETF
WisdomTree Europe Equity Income UCITS ETF
WisdomTree US SmallCap Dividend UCITS ETF
WisdomTree US Equity Income UCITS ETF
iShares MSCI USA Quality Dividend UCITS ETF
iShares Swiss Dividend ETF CH
db x-trackers MSCI North America High Dividend Yield Index UCITS ETF DR
Lyxor SG European Quality Income UCITS ETF
SPDR S&P Pan Asia Dividend Aristocrats UCITS ETF
SPDR S&P Global Dividend Aristocrats UCITS ETF
Lyxor UCITS ETF SG Global Quality Income NTR C-GBP
Lyxor SG Global Quality Income NTR UCITS ETF—D- EUR
LYXOR UCITS ETF SG GLOBAL QUALITY INCOME
SPDR S&P Euro Dividend Aristocrats UCITS ETF
SPDR S&P UK Dividend Aristocrats UCITS ETF
iShares EM Dividend UCITS ETF
SPDR S&P US Dividend Aristocrats UCITS ETF

SPDR S&P Emerging Markets Dividend UCITS ETF
 ComStage ETF DivDAX TR UCITS ETF
 iShares STOXX Global Select Dividend 100 UCITS DE
 Deka EURO STOXX® Select Dividend 30 UCITS ETF
 Deka DAXplus Maximum Dividend UCITS ETF
 AMUNDI ETF MSCI Europe High Dividend Factor UCITS ETF—C
 Amundi ETF MSCI Emu High Dividend UCITS ETF
 ComStage ETF EURO STOXX Select Dividend 30 NR UCITS ETF
 LYXOR STOXX EUROPE SELECT DIVIDEND 30 UCITS ETF
 iShares Asia Pacific Dividend UCITS ETF
 iShares Dow Jones Asia Pacific Select Dividend 3 UCITS DE
 iShares UK Dividend UCITS ETF
 iShares Euro Dividend UCITS ETF EUR Dist
 iShares Dow Jones U.S. Select Dividend UCITS ETF DE
 iShares EURO STOXX Select Dividend 30 UCITS ETF DE
 iShares STOXX Europe Select Dividend 30 UCITS ETF DE
 iShares DivDAX UCITS ETF DE

Low Volatility (19 cases)

DB X-Trackers MSCI USA Minimum Volatility UCITS ETF (DR) 1D
 db x-trackers MSCI EMU Minimum Volatility UCITS ETF (DR) 1D
 Source RBIS Equal Risk Equity US UCITS ETF
 BNP PARIBAS EASY Equity Low Vol US UCITS ETF
 BNP PARIBAS EASY Equity Low Vol Europe UCITS ETF
 Source RBIS Equal Risk Equity Europe UCITS ETF
 OSSIAM US Minimum Variance NR UCITS ETF 1D
 db x-trackers MSCI World Minimum Volatility UCITS ETF DR
 OSSIAM ETF EUROPE MINIMUM VARIANCE NR 2C
 iShares Edge S&P 500 Minimum Volatility UCITS ETF
 iShares Edge MSCI Europe Minimum Volatility UCITS ETF
 iShares Edge MSCI World Minimum Volatility UCITS ETF
 iShares Edge MSCI Europe Minimum Volatility UCITS ETF
 OSSIAM ETF EMERGING MARKETS MINIMUM VARIANCE USD
 OSSIAM ETF EMERGING MARKETS MINIMUM VARIANCE EUR
 OSSIAM ETF FTSE 100 MINIMUM VARIANCE
 OSSIAM US MINIMUM VARIANCE ESG NR UCITS ETF 1C USD
 OSSIAM US MINIMUM VARIANCE ESG NR UCITS ETF 1C EUR
 OSSIAM ETF EUROPE MINIMUM VARIANCE NR 1C

Value (9 cases)

iShares Edge MSCI USA Value Factor UCITS ETF
 BNP PARIBAS EASY Equity Value Europe UCITS ETF
 First Trust US IPO Index UCITS ETF
 OSSIAM SHILLER BARCLAYS CAPE US SECTOR VALUE TR USD
 OSSIAM SHILLER BARCLAYS CAPE US SECTOR VALUE TR EUR
 iShares Edge MSCI Europe Value Factor UCITS ETF
 Ossiham Shiller Barclays Cape Europe Sector Value TR
 iShares Edge MSCI World Value Factor UCITS ETF
 Lyxor UCITS ETF SG Global Value Beta

Equal (18 cases)

iShares Edge MSCI USA Size Factor UCITS ETF
iShares Ageing Population UCITS ETF
iShares Healthcare Innovation UCITS ETF
iShares Digitalisation UCITS ETF
THINK MORNINGSTAR NORTH AMERICA EQUITY UCITS ETF
VanEck Vectors Morningstar US Wide Moat UCITS ETF
db x-trackers FTSE 100 Equal Weight UCITS ETF DR
iShares Europe Size Factor UCITS ETF
iShares Edge MSCI World Size Factor UCITS ETF
Think European Equity UCITS ETF
db x-trackers S&P 500 Equal Weight UCITS ETF DR—1C
LYXOR PEA WORLD WATER UCITS ETF
LYXOR PEA NEW ENERGY UCITS ETF
ETFS US Energy Infrastructure MLP GO UCITS ETF
THINK Sustainable World UCITS ETF
OSSIAM Stoxx Europe 600 Equal Weight NR
Think Global Equity UCITS ETF
ComStage ETF NYSE Arca Gold BUGS UCITS ETF

Fundamentals (14 cases)

WisdomTree Eurozone Quality Dividend Growth UCITS ETF
WisdomTree Global Quality Dividend Growth UCITS ETF
WisdomTree US Quality Dividend Growth UCITS ETF
First Trust United Kingdom AlphaDEX UCITS ETF
First Trust US Large Cap Core AlphaDEX UCITS ETF
PowerShares FTSE RAFI Emerging Markets UCITS ETF
PowerShares FTSE RAFI All World 3000 UCITS ETF
Deka STOXX Europe Strong Growth 20 UCITS ETF
Deka STOXX Europe Strong Value 20 UCITS ETF
Deka STOXX Europe Strong Style Composite 40 UCITS ETF
PowerShares FTSE RAFI Europe Mid-small UCITS ETF
PowerShares FTSE RAFI UK 100 UCITS ETF
PowerShares FTSE RAFI Europe UCITS ETF
PowerShares FTSE RAFI US 1000 UCITS ETF

Multifactor (21 cases)

Lyxor J.P. Morgan Multifactor World Index UCITS ETF
PowerShares EURO STOXX High Dividend Low Volatility UCITS ETF
BMO MSCI USA Income Leaders GBP Hedged UCITS ETF
BMO MSCI Europe ex-UK Income Leaders (GBP Hedged) UCITS ETF
BMO MSCI UK Income Leaders UCITS ETF
BMO MSCI USA Income Leaders UCITS ETF
BMO MSCI Europe ex-UK Income Leaders UCITS ETF
Lyxor JP Morgan Multifactor Europe Index UCITS ETF -C- EUR
iShares Edge MSCI Europe Multifactor UCITS ETF EUR Acc
iShares Edge MSCI USA Multifactor UCITS ETF USD Acc
iShares Edge MSCI World Multifactor UCITS ETF
MS Scientific Beta US Equity Factors UCITS ETF
First Trust Japan AlphaDEX UCITS ETF
Source Goldman Sachs Equity Factor Index Europe UCITS ETF
First Trust Large Cap Core AlphaDEX UCITS ETF
First Trust Eurozone AlphaDEX UCITS ETF

Amundi ETF Global Equity Multi Smart Allocation Scientific Beta UCITS ETF-B USD
 Amundi ETF Global Equity Multi Smart Allocation Scientific Beta UCITS ETF-A EUR
 MS Scientific Beta Global Equity Factors UCITS ETF
 Source Goldman Sachs Equity Factor Index World UCITS ETF
 PowerShares Dynamic US Market UCITS ETF

Quality (4 cases)

iShares Edge MSCI USA Quality Factor UCITS ETF
 BNP PARIBAS EASY Equity Quality Europe UCITS ETF
 iShares Edge MSCI Europe Quality Factor UCITS ETF
 iShares Edge MSCI World Quality Factor UCITS ETF

Momentum (4 cases)

iShares Edge MSCI USA Momentum Factor UCITS ETF
 BNP PARIBAS EASY Equity Momentum Europe UCITS ETF
 iShares Edge MSCI Europe Momentum Factor UCITS ETF
 iShares Edge MSCI World Momentum Factor UCITS ETF

Buyback (3 cases)

AMUNDI ETF MSCI EUROPE BUYBACK UCITS ETF
 Amundi ETF S&P 500 Buyback UCITS ETF—EUR
 Amundi ETF S&P 500 Buyback UCITS ETF—USD

Appendix B. List of Cap-Weighted Benchmarks

Benchmark (40 cases)

MSCI USA Index
 MSCI EMU Index
 MSCI World Index
 MSCI World Health Care Index
 MSCI World Information Technology Index
 Russell 1000 Index
 MSCI Europe Index
 MSCI UK Value Weighted Index
 MSCI Emerging Markets Index
 MSCI World Value Index
 MSCI Europe High Dividend Yield Index
 FSE DAX
 MSCI Europe ex-UK Index
 MSCI UK Index
 MSCI AC Asia Ex Japan Index
 FTSE All-Share Index
 MSCI World High Dividend Yield Index
 FTSE 100 Index
 Topix
 MSCI ACWI ex USA Index
 MSCI Europe SMID Cap Index
 MSCI Europe Value
 MSCI Emerging Markets SMID Cap Index
 MSCI Europe Small Cap Index
 Russell 2000 Index
 Russell 1000 Value Index
 MSCI World Small Cap Index

S&P Global Water Index
 S&P Global Clean Energy Index
 MSCI World Energy Index
 MSCI Switzerland Index
 MSCI North America
 MSCI AC Asia Pacific Index
 EMIX Global Mining Global Gold Index
 FTSE Emerging All Cap Index
 FTSE Global All Cap Index
 MSCI Europe Growth Index
 MSCI Europe Value Index
 FTSE RAFI Developed ex US Mid Small 1500 Index
 FTSE 350 ex Investment Trusts Index

Appendix C. Summary of the Average AV for Each SB Category Relative to Their Respective Benchmarks over Time

Date	Dividend	Low Volatility	Value	Equal	Fundamentals	Multifactor	Quality	Momentum	Buyback
2006	0.0159	-	-	-	-	-	-	-	-
2007	0.0160	-	-	-	-	-	-	-	-
2008	0.0322	-	-	-	0.0067	0.0061	-	-	-
2009	0.0375	-	-	-	0.0303	−0.0454	-	-	-
2010	−0.0417	-	-	-	−0.0380	−0.0266	-	-	-
2011	−0.0299	-	-	−0.3264	−0.0489	0.0221	-	-	-
2012	−0.0058	−0.0197	-	−0.0332	−0.0325	−0.0222	-	-	-
2013	0.0051	0.0005	-	0.0421	0.0100	0.0888	-	-	-
2014	0.0049	−0.0143	-	0.0283	0.0015	0.0148	-	-	-
2015	0.0027	−0.0163	0.0375	0.0635	−0.0153	−0.0230	−0.0026	−0.0152	-
2016	−0.0002	−0.0265	0.0212	0.0229	−0.0015	0.0075	−0.0042	−0.0134	0.0499
2017	0.0211	0.0074	0.0169	0.0084	0.0228	0.0193	0.0121	0.0182	0.0349

This table quantifies the relative differences in the average AV of the SB ETFs versus their benchmarks. In this instance, bold faced values show that the average AV is less than the benchmarks, otherwise the average AV is greater than the benchmarks.

Appendix D

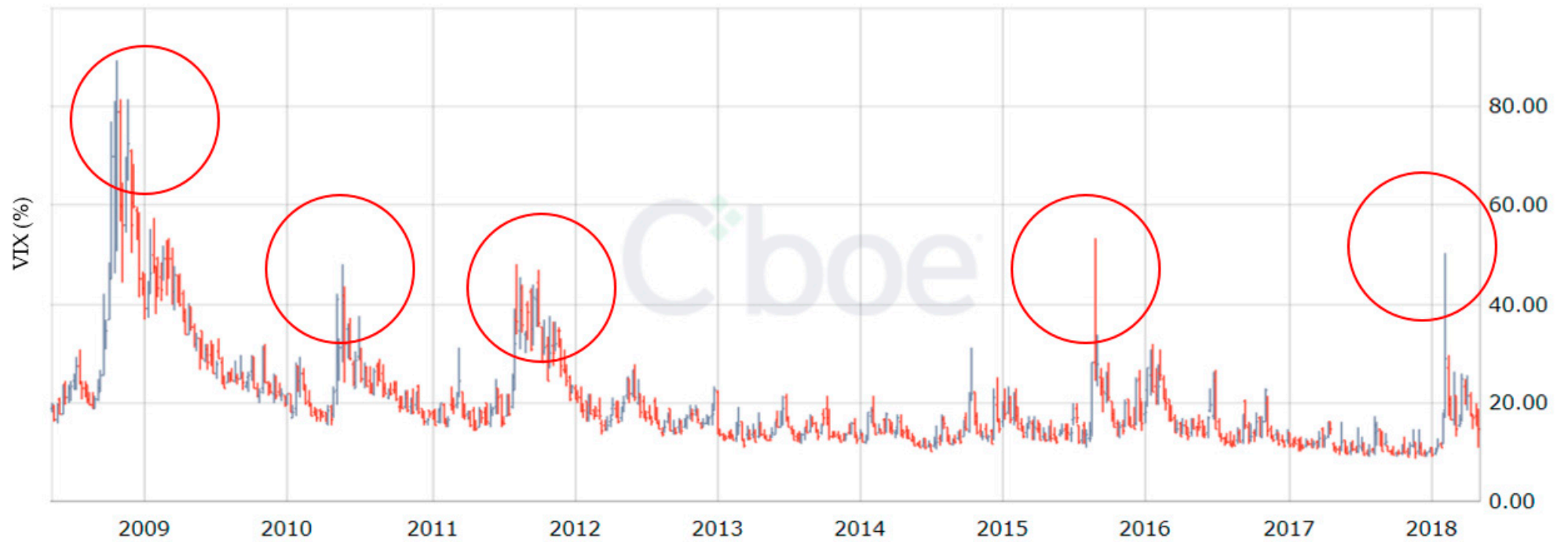


Figure A1. Volatility Index VIX (CBOE Market Volatility). (Source: CBOE.)

Appendix E

Table A1. Consolidated three-factor model regression coefficients.

Factor		R ²	Sig. F	Alpha × 10 ³	p-Value	Market Beta	p-Value	Size Beta × 10 ³	p-Value	Value Beta × 10 ³	p-Value
Dividend	Average	65%	2.5731×10^{-2}	−1.4757	0.33182	0.76790	4.3626×10^{-2}	−2.7964	0.2191	−0.18148	0.3258
	Median	68%	5.2683×10^{-12}	−1.6847	0.27788	0.89628	1.1753×10^{-12}	−1.6180	0.1275	−0.16832	0.2954
Low Volatility	Average	77%	2.5818×10^{-4}	0.21095	0.42892	0.75183	5.4104×10^{-4}	−3.1493	0.2153	−2.8586	0.1398
	Median	82%	3.6311×10^{-15}	0.18720	0.31310	0.75254	2.3480×10^{-14}	−2.5926	0.0433	−3.3469	0.0056
Value	Average	80%	5.2755×10^{-5}	0.36021	0.35655	1.10650	1.0215×10^{-5}	−0.56776	0.2435	0.035878	0.4263
	Median	86%	2.6200×10^{-7}	2.2631	0.23135	1.08080	5.2000×10^{-8}	0.58598	0.1958	−0.61481	0.3796
Equal	Average	66%	4.1294×10^{-2}	−0.91903	0.40276	0.85002	2.7165×10^{-2}	−0.45539	0.2702	−1.0061	0.4299
	Median	66%	3.9420×10^{-6}	−0.61255	0.42503	0.86665	1.3810×10^{-6}	−0.67843	0.1230	−0.21864	0.4900
Fundamentals	Average	74%	4.3400×10^{-7}	0.39484	0.41610	0.81593	1.1590×10^{-6}	−0.55701	0.1945	0.72174	0.1780
	Median	77%	7.9717×10^{-25}	0.24952	0.31640	0.74982	3.4825×10^{-20}	−1.3613	0.0981	1.1243	0.0169
Multifactor	Average	68%	1.2645×10^{-2}	2.7242	0.35363	0.77439	5.6590×10^{-2}	−1.5965	0.1995	−0.82381	0.3500
	Median	84%	1.0000×10^{-9}	−0.59370	0.32870	0.88051	5.2228×10^{-11}	−0.03807	0.1220	−1.2253	0.3417
Quality	Average	93%	3.0770×10^{-6}	−0.77241	0.65472	1.03230	1.0160×10^{-6}	−0.51532	0.5506	−2.2643	0.0793
	Median	93%	2.8900×10^{-7}	−0.60921	0.67508	0.99748	1.7000×10^{-7}	−0.05868	0.6196	−2.0221	0.0630
Momentum	Average	74%	1.6335×10^{-2}	5.9749	0.25621	0.78741	3.4174×10^{-2}	−1.6776	0.3877	−3.5268	0.0848
	Median	78%	1.5878×10^{-4}	3.5512	0.27313	0.85953	1.0606×10^{-4}	−1.1620	0.3942	−3.3563	0.0705
Buyback	Average	78%	3.2320×10^{-6}	−2.3925	0.60037	1.17260	1.3940×10^{-6}	0.91185	0.1701	1.3891	0.4419
	Median	83%	9.3960×10^{-12}	−2.0408	0.74141	1.15150	1.1444×10^{-12}	2.8096	0.1876	0.81777	0.4114

Appendix F

Table A2. Consolidated four-factor model regression coefficients.

Factor		R ²	Sig. F	Alpha × 10 ³	p-Value	Market Beta	p-Value	Size Beta × 10 ³	p-Value	Value Beta × 10 ³	p-Value	Momentum Beta × 10 ³	p-Value
Dividend	Average	68%	2.327×10^{-2}	−0.932	0.3956	0.7476	7.308×10^{-1}	−2.9524	0.2225	−0.5677	0.3492	−0.7386	0.3609
	Median	71%	4.737×10^{-11}	−1.188	0.2980	0.8396	8.251×10^{-1}	−1.7104	0.1483	−0.8338	0.2864	−0.7156	0.2840
Low Volat.	Average	79%	1.220×10^{-4}	0.1031	0.4772	0.7438	5.132×10^{-4}	−2.9419	0.2461	−2.5918	0.2051	−0.3209	0.3393
	Median	85%	1.149×10^{-14}	0.0843	0.3150	0.7770	2.078×10^{-14}	−2.2873	0.0433	−2.8711	0.0258	0.4957	0.2568
Value	Average	80%	1.145×10^{-4}	1.0366	0.3424	1.0760	7.925×10^{-5}	−0.4991	0.2648	−0.2465	0.4369	−0.9609	0.6552
	Median	86%	1.449×10^{-6}	2.7936	0.2427	1.0863	2.680×10^{-7}	0.5416	0.1938	−0.6911	0.4466	−0.6613	0.6468
Equal	Average	69%	4.254×10^{-2}	0.7658	0.4103	0.8054	3.503×10^{-2}	−0.7602	0.2573	−2.1760	0.3787	−1.3795	0.3404
	Median	69%	3.012×10^{-6}	0.5285	0.3700	0.8030	1.852×10^{-5}	−1.7596	0.1471	−1.3058	0.2798	−0.9692	0.2886
Fundamentals	Average	75%	7.080×10^{-7}	0.1231	0.4226	0.8140	2.480×10^{-7}	−0.6468	0.1768	0.5463	0.1989	0.0180	0.3223
	Median	77%	5.831×10^{-24}	0.3039	0.3748	0.7501	4.766×10^{-19}	−1.6124	0.1121	1.0678	0.1322	−0.4850	0.3092
Multifactor	Average	71%	1.566×10^{-2}	2.3309	0.4066	0.7950	3.769×10^{-2}	−1.5053	0.2153	−0.5418	0.3889	0.4299	0.5122
	Median	85%	7.310×10^{-9}	−0.583	0.4103	0.8453	1.000×10^{-9}	−0.2428	0.1260	−0.8303	0.3691	0.2694	0.4935
Quality	Average	94%	1.649×10^{-5}	−0.762	0.5320	1.0375	4.026×10^{-6}	−0.4856	0.4378	−2.3343	0.1252	0.0997	0.2758
	Median	93%	4.090×10^{-7}	−0.225	0.5214	1.0365	1.370×10^{-7}	−0.2337	0.4166	−1.9437	0.1165	−0.6339	0.2467
Momentum	Average	85%	2.797×10^{-3}	2.8302	0.5022	0.9505	5.352×10^{-3}	−1.5571	0.3111	−2.2107	0.2635	4.9015	0.0076
	Median	86%	1.994×10^{-5}	0.4764	0.4976	0.9790	4.626×10^{-6}	−0.4453	0.2926	−1.2446	0.2762	4.9683	0.0052
Buyback	Average	78%	1.232×10^{-5}	−1.589	0.6885	1.1460	9.713×10^{-6}	0.8281	0.1756	0.8437	0.6202	−0.8735	0.6462
	Median	83%	6.623×10^{-11}	−0.851	0.8998	1.1167	2.431×10^{-11}	2.7471	0.2045	0.4599	0.7019	−0.7398	0.6600

Note

- ¹ The Fama–French online data library can be found at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html (accessed on 21 February 2021).

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