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Performance and Factor Exposures of Smart Beta ETFs

Evidence from U.S. Markets, 2018–2023

Accounting and Finance
Bachelor's thesis

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Smart Beta investing is a strategy that combines elements of passive and active management by tracking rules-based indices that tilt toward specific factors designed to capture risk premia associated with market anomalies historically linked to higher returns. These strategies aim to enhance returns, improve diversification, or reduce risk relative to traditional market-capitalization-weighted approaches.

This thesis investigates the performance and factor exposures of U.S.-listed equity Smart Beta ETFs across three commonly studied strategies: Size, Value, and Momentum. Equally weighted portfolios are constructed for each strategy and assessed against a broad market benchmark. The analysis covers the period from January 2018 to December 2023 and is further divided to three sub-periods: pre-COVID (2018–2019), COVID crisis (2020), and post-COVID (2021–2023).

The performance of Smart Beta portfolios is assessed using mean excess returns, alongside regression-based analysis employing the Fama-French three-factor model and the Carhart four-factor model to assess whether these strategies deliver abnormal returns (alpha) and to evaluate their factor exposure. In addition, Sharpe and Sortino ratios are used to provide further insight into risk-adjusted performance.

The results show that while Smart Beta ETFs can outperform the market benchmark in terms of mean excess returns during certain sub-periods, none of the portfolios generate statistically significant alpha over full sample period or within any sub-period. This indicates that the returns are largely explained by exposure to established risk factors. The portfolios successfully align with their intended factor tilts–particularly the Size and Momentum strategies–but often exhibit unintended exposures, and consistently high sensitivity to the market factor. The Sharpe and Sortino ratios reinforce these findings by showing that Smart Beta portfolios rarely outperform the benchmark on a risk-adjusted basis.

Overall, these findings suggest that although Smart Beta ETFs offer targeted exposure to systematic risk premia, they do not consistently generate excess returns beyond what is justified by their factor risk. These results support existing literature and highlight the importance of evaluating Smart Beta strategies not only by their labels or construction methodology but through their realized risk-adjusted performance.

Key words: Smart Beta, Exchange Traded Funds (ETFs), Factor Investing, Size, Value, Momentum, Risk-Adjusted Performance, Asset Pricing Models, Fama-French Model, Carhart Model

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Smart Beta -sijoittaminen on strategia, joka yhdistää passiivisen ja aktiivisen sijoittamisen piirteitä seuraamalla sääntöpohjaisia indeksejä, jotka painottavat tiettyjä faktoreita. Näiden faktoreiden tavoitteena on hyödyntää havaittuja markkina-anomalioita, joiden on historiallisesti osoitettu olevan yhteydessä korkeampiin tuottoihin. Strategioiden pyrkimyksenä on lisätä tuottoja, parantaa hajautusta tai vähentää riskiä verrattuna perinteisiin markkina-arvopainotteisiin lähestymistapoihin.

Tässä kandidaatintutkielmassa tarkastellaan Yhdysvalloissa listattujen osakepohjaisten Smart Beta ETF:ien tuottoja ja faktorialtistuksia kolmen laajalti tutkitun strategian – koko (Size), arvo (Value) ja momentum – osalta. Jokaiselle strategialle muodostetaan tasapainotettu portfolio, joita verrataan laajaan markkinaindeksiin. Tutkimus kattaa ajanjakson tammikuusta 2018 joulukuuhun 2023 ja jakautuu kolmeen osa-ajanjaksoon: ennen COVID-pandemiaa (2018–2019), pandemian aikana (2020) ja sen jälkeen (2021–2023).

Smart Beta portfolioiden tuottoja arvioidaan keskimääräisten ylituottojen sekä regressioanalyysin avulla hyödyntäen Fama-French kolmifaktorimalia ja Carhartin nelifaktorimallia. Tavoitteena on selvittää, tuottavatko strategiat epänormaaleja tuottoja (alfaa) ja analysoida niiden faktorialtistuksia. Lisäksi riskikorjatun tuoton arvioimiseksi hyödynnetään Sharpen ja Sortinon tunnuslukuja.

Tulokset osoittavat, että vaikka Smart Beta -strategiat voivat tuottaa tietyillä ajanjaksoilla markkinaindeksiä korkeampia ylituottoja, yksikään portfolio ei tuottanut tilastollisesti merkitsevää alfaa koko tarkastelujaksolla tai yksittäisillä osa-ajanjaksoilla. Tämä viittaa siihen, että tuotot selittyvät pääasiassa altistumisella tunnetuille riskitekijöillä. Portfoliot painottuvat tavoitelluille faktoreille – erityisesti arvo- ja momentum-strategiat – mutta niissä havaitaan usein myös ei-toivottuja altistuksia sekä voimakasta herkkyyttä markkinafaktorille. Sharpen ja Sortinon tunnusluvut tukevat näitä havaintoja osoittaen, että Smart Beta -portfoliot suoriutuvat harvoin vertailuindeksiä paremmin riskikorjatuin mittarein.

Yhteenvetona voidaan todeta, että vaikka Smart Beta ETF:t tarjoavat kohdennettua altistumista systemaattisille riskipreemioille, ne eivät johdonmukaisesti tuota ylituottoja suhteessa niihin liittyviin faktoririskeihin. Tulokset tukevat aiempaa kirjallisuutta ja korostavat, että Smart Beta -strategioita tulisi arvioida ennen kaikkea toteutuneen riskikorjatun tuoton perusteella, ei pelkästään niiden nimen tai rakenteellisen lähestymistavan perusteella.

Avainsanat: Smart Beta, Exchange Traded Funds (ETFs), Faktorisijoittaminen, Koko, Arvo, Momentum, Riskikorjattu tuotto, Hinnoittelumallit, Fama-French malli, Carhart malli

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1 Introduction

1.1 Background and Motivation

Over the past decade, Exchange-Traded Funds (ETFs) have become a significant part of the global financial landscape. Their popularity has continued to rise in recent years, largely due to their transparency, cost-efficiency, diversification, and tax advantages. Most ETFs are designed to replicate the performance of predetermined indices, offering investors broad market exposure at relatively low cost. (Joshi & Dash 2024.) However, since these ETFs track passive indices, they generally do not offer the potential for outperformance. In contrast, active fund managers aim to outperform the market, but often struggle to do so consistently, especially after accounting for higher management fees and transaction costs (Malhotra 2024).

As a result, investors have increasingly sought alternative strategies that might provide enhanced returns without the high costs associated with traditional active management. One such approach is Smart Beta investing, which has experienced rapid growth over the past decade. As of June 2024, global assets in Smart Beta strategies had grown at a five-year annualized rate of 22.5%. (Jacobs et al. 2025.)

Smart Beta strategies are typically positioned between traditional passive and active management, as they combine elements of both approaches. Like passive investing, they rely on transparent and rules-based methodologies. However, they differ from traditional market capitalization weighting by constructing portfolios that systematically target specific factors. These factors—such as size, value, momentum, quality, and low volatility—have been associated with long-term risk-adjusted excess returns in academic literature. (Kahn & Lemmon 2016.) While these factor premia were previously accessible primarily through active strategies, Smart Beta ETFs now allow investors to capture them at a fraction of the cost (Le 2023).

1.2 Purpose of the Thesis

The aim of this thesis is to evaluate the performance and factor exposures of selected Smart Beta strategies using U.S.-listed equity ETFs. Specifically, the study focuses on three widely applied factor-based strategies: Size, Value, and Momentum. These strategies were selected based on their strong foundations in well-documented market anomalies and extensive academic literature. Each strategy is implemented using an equally weighted portfolio, comprising 13 ETFs for the Size portfolio, 15 for Value, and 11 for Momentum.

The performance of these portfolios is first assessed by comparing their excess returns–defined as total return minus the risk-free rate–to the excess return of the selected benchmark (SPDR S&P 500 ETF). In addition, the thesis applies two well-established asset pricing models: the Fama-French three-factor model and the Carhart four-factor model. These models enable an evaluation of risk-adjusted excess returns–also referred to as abnormal returns, which represents returns beyond those explained by exposure to known risk factors–as well as measuring each portfolio's exposure to systematic risk factors. In addition to regression analysis, Sharpe and Sortino ratios are used to further evaluate risk-adjusted performance. The analysis covers the full sample period from January 2018 to December 2023 and further investigates three distinct sub-periods—pre-COVID (2018–2019), the COVID crisis (2020), and post-COVID recovery (2021–2023)—to examine how performance and factor exposures vary across different market conditions.

This thesis seeks to answer the following research questions:

1. Do Size, Value, and Momentum Smart Beta portfolios outperform the market benchmark in terms of mean excess returns and risk-adjusted returns?
2. To what extent do the selected Smart Beta portfolios load on their intended factor exposures?
3. How do the returns and factor exposures of these strategies change across different market conditions?

By addressing these questions, the thesis aims to provide insights into the effectiveness and limitations of factor-based ETF strategies from both a performance and risk-factor perspective.

1.3 Structure

Chapter 2 provides the theoretical foundation for the study, including a discussion of the Efficient Market Hypothesis and the main asset pricing models. These include the traditional Capital Asset Pricing Model (CAPM), and the factor-based models used in the analysis. Chapter 3 introduces the concept of Smart Beta, its definitions, and how it differs from traditional active and passive investment strategies.

Chapter 4 marks the beginning of the empirical part of the thesis. It outlines the data and methodology, including portfolio construction, ETF and benchmark selection, and the analytical approach. Specifically, it describes how the performance of the Smart Beta strategies is evaluated using the Fama-French three-factor model and the Carhart four-factor model. Chapter 5 presents the results of the empirical analysis. It includes descriptive statistics, and regression results for both the full sample period and three market sub-periods, highlighting how performance and factor exposures vary over time.

Finally, Chapter 6 concludes the thesis by interpreting the results in relation to the research questions and theoretical background. It also discusses the study's limitations and proposes areas for future research.

In this thesis, artificial intelligence (AI) was used for language editing and refinement, as well as for developing ideas and structuring the content.

2 Asset Pricing Models

2.1 Efficient Market Hypothesis

The Efficient Market Hypothesis (EMH) is a cornerstone of modern financial theory and serves as a theoretical foundation for this thesis. EMH was first formally proposed by Eugene Fama in 1970, although the idea has a long history dating back to the early 1900s when Louis Bachelier introduced the concept of the random walk theory, which suggests that price movements are essentially unpredictable and follow a stochastic process (Fama 1970).

According to Fama (1970), a market is considered efficient if security prices fully reflect all available information at all times. When new information becomes available, it quickly spreads across the market and is almost instantly reflected in security prices. Therefore, investors cannot achieve higher returns than a randomly selected portfolio of stocks using technical or fundamental analysis, particularly when accounting for similar risk levels. (Malkiel 2003.)

Fama (1970) introduced three forms of market efficiency:

- Weak form: All past trading information, such as historical prices and volumes, are already reflected in current prices. Therefore, technical analysis should not provide consistent excess returns.
- Semi-strong form: In addition to past prices, all publicly available information is reflected in prices. Thus, fundamental analysis is also ineffective.
- Strong form: All information–public and private, including insider information–are incorporated into prices.

Fama (1970) and Jensen (1978) noted that the strong form of efficiency should be viewed as a theoretical benchmark rather than an absolute description of real-world markets.

Despite its broad acceptance, EMH has faced criticism, particularly due to documented market anomalies. For example, Basu (1977) identified an example of value anomaly, indicating that stocks with low price-to-earnings (P/E) ratios tend to outperform those with high P/E ratios. Similarly, Banz (1981) documented the size anomaly, showing that smaller firms tend to earn higher risk-adjusted returns compared to larger firms. These empirical findings challenge the assumption of fully efficient markets–particularly under semi-strong and strong forms–by suggesting that some information may not be immediately or fully incorporated into prices. However, according to

Malkiel (2003), although markets may not be perfectly efficient, they are generally more efficient than some of the literature suggests. Malkiel further argues that anomalies are often short-lived and lack robustness, making it difficult for investors to exploit them reliably and systematically achieve excess returns.

While debates around EMH continue, the hypothesis remains a fundamental framework in asset pricing theory. It has influenced how markets are understood and laid the groundwork for more advanced models that incorporate multiple risk factors. The following sections introduce these asset pricing models, beginning with the Capital Asset Pricing Model (CAPM).

2.2 Capital Asset Pricing Model (CAPM)

The Capital Asset Pricing Model (CAPM) is among the most widely recognized and influential asset pricing models used in finance. CAPM provides a theoretical framework for understanding the relationship between risk and expected return. The first formal version of the model was introduced by Sharpe (1964) and Lintner (1965), and is commonly referred to as the Sharpe-Litner CAPM, and is the most frequently used version of the model. Their model builds on the principles of modern portfolio theory introduced by Markowitz (1952), emphasizing the role of diversification in reducing portfolio risk. The later development of CAPM formalized the distinction between systematic and unsystematic risk.

The model proposes that the expected return of an asset is assessed by its sensitivity to market risk, often referred as systematic risk, which cannot be diversified away. CAPM is generally expressed by the following equation:

$$E(R_i) = R_f + \beta_i(E(R_m) - R_f)$$

where $E(R_i)$ represents the expected return of asset i, R_f is the risk-free rate of return, β_i is the asset's beta, which measures its exposure to systematic market risk, and $E(R_m)$ is the market portfolio's expected return.

The CAPM relies on several simplifying assumptions. It assumes that investors are rational and risk-averse, aiming to maximize expected utility. All investors have homogeneous expectations about returns and variances of assets. Markets are assumed to be perfectly competitive and frictionless–there are no taxes or transaction costs, and all investors can borrow and lend at the risk-free rate. While these assumptions provide theoretical clarity, they also limit the model's realism and contribute to its empirical shortcomings. (Sharpe 1964 & Lintner 1965.)

CAPM has been widely applied in academic research. However, its ability to accurately predict assets returns based solely on beta has been questioned. Early empirical studies by Black et al. (1972) found that, contrary to the model's predictions, low-beta securities yielded higher returns than expected, while high-beta securities underperformed. This discrepancy led to the identification of the low-beta anomaly. Additionally, Fama and MacBeth (1973) confirmed a positive risk–return relationship, but also noted that this relationship was not perfectly linear and that other factors could influence asset returns.

Further research provided additional evidence of CAPM's limitations. For instance, Rosenberg et al. (1985) demonstrated that stocks with high book-to-market (B/M) ratios earned higher returns than those with low B/M ratios, a phenomenon known as the value anomaly. As previously mentioned in Section 2.1, Banz (1981) provided evidence for the size anomaly and Basu (1977) provided evidence of a value effect through connection between returns and P/E ratios. However, Reinganum (1981) found that the P/E effect and the value anomaly appear to be closely, and both are largely influenced by the size effect. His results that these anomalies may stem from a common set of missing risk factors more closely associated with firm size than valuation ratios alone.

These findings have led to the development of alternative asset pricing models that incorporate additional factors beyond market risk, beta. The Fama-French three-factor model and the Carhart four-factor model–which build on these insights–will be discussed in the following sections. Despite its limitations, CAPM continues to be widely used in finance due to its simplicity and conceptual clarity.

2.3 Fama-French three-factor Model

In response to the empirical findings that challenged the explanatory power of CAPM, Fama and French (1992) introduced a new framework to better explain asset returns. Their research demonstrated that factors beyond market risk, particularly firm size and book-to-market (B/M), had significant explanatory power in explaining the cross-section of stock returns. These findings led to the development of the Fama-French three-factor model (Fama & French 1993), which extends CAPM by incorporating two additional factors: size and value.

The three-factor model is expressed as follows:

$$E(R_i) = R_f + \beta_i\big(E(R_m) - R_f\big) + s_i SMB + h_i HML$$

where $E(R_i)$ represents the expected return of asset i, R_f is the risk-free rate, β_i is the asset's beta, which measures its exposure to systematic market risk, and $E(R_m)$ is the market portfolio's expected return. The additional factors, SMB (small minus big) and HML (high minus low), capture the size and value premiums, respectively. The coefficients s_i and h_i are factors loadings that represent the asset's sensitivity to the size and value factors. The size premium (SMB) reflects the historical tendency for small-cap stocks to outperform large-cap stocks, while the value premium (HML) reflects the returns of high book-to-market (value) firms compared to low book-to-market (growth) firms (Fama & French 1993).

Empirical tests by Fama and French (1993) showed that their model provided a significantly improved explanation of asset returns when compared to CAPM. In particular, the model better captured the risk-return relationship for portfolios sorted by size and book-to-market ratios. Later research also found that the model could explain other anomalies, such as the earnings-to-price effect, through its size and value components (Fama & French 1996).

However, the model is not without criticisms. For instance, Loughran (1997) noted that the explanatory power of the HML and SMB varies across different time periods and markets. Furthermore, some evidence suggests that stock returns may be better explained by firm-specific characteristics rather than by exposure to systematic risk factors, challenging the notion that SMB and HML factors fully represent compensation for systematic risk (Daniel & Titman 1997).

While the Fama-French three-factor model marked a major improvement over CAPM, later research suggested that momentum was another important factor in explaining asset returns–leading to further extensions such as the Carhart four-factor model.

2.4 Carhart four-factor Model

Jegadeesh and Titman (1993) find that investment strategies involving the purchase of past winners and the sale of past losers yield significantly abnormal returns over 3- to 12-month holding periods. Their study further demonstrates that these returns are not explained by exposure to systematic risk or the delayed adjustment of stock prices to known risk factors. This persistent return pattern is referred to as momentum. Earlier research by De Bondt and Thaler (1985) documented a long-term reversal effect. They found that stocks which had previously underperformed the market (losers) tended to outperform in subsequent years, while past winners generally underperformed. Their results suggested that investor overreaction to unexpected information can drive predictable return patterns, challenging the assumptions of market efficiency.

While the Fama-French three-factor model has improved explanatory power of asset pricing models compared to CAPM, and is able to capture the long-term reversal effect, it fails to capture short-term trends in stock returns. Momentum, which refers to the tendency of past winners to continue outperforming and past losers to continue underperforming in the near term, became well documented anomaly. (Fama & French 1996.)

Motivated by these findings, Carhart (1997) extended the Fama-French framework by introducing a fourth factor to account for momentum. The resulting Carhart four-factor model incorporates market, size, value, and momentum effects into a single pricing model.

Carhart's four-factor model is expressed as follows:

$$E(R_i) = R_f + \beta_i\big(E(R_m) - R_f\big) + s_i SMB + h_i HML + m_i(UMD)$$

where $E(R_i)$ represents the expected return of asset i, R_f is the risk-free rate, β_i is the asset's beta, which measures its exposure to systematic market risk, and $E(R_m)$ is the market portfolio's expected return. SMB, HML, and UMD represent the size, value, and momentum premiums, respectively. The coefficients s_i, h_i, and m_i are asset's loadings on these factor premiums. The momentum factor UMD (up minus down) is constructed by taking the return differential between past winners and losers.

Carhart (1997) emphasizes that mutual funds with high returns in the previous year tend to exhibit above-average expected returns in the following year. However, this momentum effect tends to be short-lived and inconsistent across time, meaning it does not persist systematically in subsequent years.

Overall, the Carhart four-factor model provides a more comprehensive framework for explaining asset returns by accounting for momentum alongside market, size, and value factors. The inclusion of the UMD factor allows researchers and practitioners to better capture short-term return dynamics that previous models failed to explain.

3 Smart Beta

3.1 Definition

Smart Beta is an investment approach that combines elements of both passive and active investing. It aims to enhance returns, improve diversification, or reduce risk by constructing portfolios based on specific factors rather than traditional market capitalization weighting. While Smart Beta strategies follow systematic and transparent rules similar to passive investing, they incorporate active management principles by tilting portfolios toward characteristics that have historically been linked to higher returns. (Kahn & Lemmon 2015 ; Malkiel 2014.)

The emergence of Smart Beta is closely tied to the development of factor investing. As discussed in Section 2, empirical research has identified persistent anomalies–such as size, value, and momentum effects–which led to the development of multi-factor models. These findings also prompted index providers to introduce products that systematically capture exposure to specific factor tilts (Hsu et al. 2012). Although Smart Beta strategies are most commonly applied in equities, they have also been extended to other asset classes such as commodities and fixed income (Arnott & Sherrerd 2022). Traditionally, it was assumed that only actively managed funds could exploit market inefficiencies. A key limitation of active management, however, was its inability to consistently outperform the market, coupled with higher management fees. This challenge motivated the development of strategies that deviate from traditional market-capitalization weighting while retaining rules-based implementation to gain systematic exposure to established risk factors in a cost-effective and transparent manner. (Hsu et al. 2012.)

Despite its widespread use, the term “Smart Beta” lacks a universally accepted definition. Market providers have adopted the label broadly, often applying it to any strategy that deviates from market-cap weighted, leading to misleading and inconsistent use of the term. (Arnott & Kose 2014.) Richard and Roncalli (2015) distinguish between two broad approaches within Smart Beta. The first one is risk-based investing, where portfolios aim to improve diversification by employing alternative weighting strategies instead of market capitalization. The second is factor-based investing, where portfolios attempt to capture risk premia beyond the market risk premium. However, Alonso and Barnes (2016) emphasize that not all alternative weighting methods qualify as Smart Beta. They define portfolios that use non-capilazation-based weighting without targeting specific factors as Alternative Beta strategies. In contrast, portfolios designed to achieve exposure to specific factors–regardless of whether they use market-cap or alternative weighting–are considered as Smart Beta strategies.

Smart Beta has also faced criticism. It is not always clear whether the excess returns stem from exposure to systematic factor risk or from market inefficiencies. In addition, Smart Beta portfolios are often concentrated in specific risk factors–such as size, value, or momentum–making them vulnerable to periods of underperformance when those factors fall out of favor. While Smart Beta strategies control risk exposures through factor definitions and transparent portfolio construction rules, a simplistic factor-based approach may fail to effectively capture intended exposures or may introduce unintended ones. (Jacobs & Levy 2014.)

To put it simply, Smart Beta represents investment strategies that systematically deviate from traditional market capitalization weighting to capture factor-based return premia. However, there is no single, universally accepted definition of Smart Beta, and the term is applied to a broad set of methodologies. This thesis does not seek to validate any particular definition but instead focuses on investment products marketed under Smart Beta label.

3.2 Smart Beta ETFs

The rise of ETFs over the last decade has been driven by their cost-efficiency, transparency, tax benefits, and accessibility for both institutional and retail investors. Among the various ETF types, Smart Beta ETFs have played a crucial role in this expansion, offering investors a structured way to gain exposure to factor-based strategies while avoiding the higher fees typically associated with active management. At the end of 2019, Smart Beta ETFs represented 22% of the total assets within the U.S. ETF market. (Le 2023.) Smart Beta strategies can be implemented through different investment vehicles such as mutual funds, but ETFs have emerged as the dominant format. At the end of 2017, 61% of Smart Beta funds were structured as ETFs, while only one was structured as an active mutual fund. (Arnott & Sherrerd 2022.) Smart Beta ETFs are typically positioned between traditional passive and active ETFs in terms of cost, reflecting their hybrid nature (Chen & Edwards 2021).

Smart Beta ETFs incorporate a wide range of factor-based strategies, each aiming to outperform the market by tilting portfolios towards characteristics historically linked to excess returns. The most commonly applied strategies include size, value, growth, momentum, and dividend yield, as well as combinations of multiple factors (Lettau & Madhavan 2018). While the broader Smart Beta universe includes a variety of alternative approaches, this thesis focuses on three widely adopted factor-based strategies: size, value, and momentum. These strategies are well-established in academic literature and are commonly available in ETF structures, making them a relevant subject for empirical analysis.

Despite their popularity, Smart Beta ETFs have faced criticism, particularly regarding the potential impact of data mining in index construction. While these ETFs are promoted as systematic and rules-based, research suggests that their pre-launch performance tends to be significantly stronger than their actual returns post-listing. Smart Beta indices often exhibit strong backtested performance, but once ETFs tracking these indices are introduced to the market, their returns tend to fall behind traditional cap-weighted indices. (Huang et al. 2024.) This raises concerns that some Smart Beta strategies may be overfitted to historical data, making them less effective in real-world applications. Additionally, factor investing itself has been questioned, as Harvey and Liu (2019) document over 400 factors published in top academic journals, raising concerns that many of them may be the result of factor and data mining rather than genuine economic relationships.

In their study on Smart Beta ETF performance, Mateus et al. (2020) examine whether these strategies deliver persistent excess returns over time. The sample covers 152 U.S. equity Smart Beta ETFs over the period from June 2000 to May 2017. The authors find that 43% of the ETFs outperformed their benchmarks based on risk-adjusted returns. Performance varied across market capitalization categories: 61% of small-cap ETFs produced positive alpha, compared to 39% of large-cap and 36% of mid-cap Smart Beta ETFs. Particularly, 58% of small-cap blend ETFs generated positive alphas, while only 11% did so in in the large-cap value category. However, it is important to note that Mateus et al. (2020) used a modified version of the Carhart four-factor model, in which the risk-free rate was replaced with each ETF's specific benchmark. Bowes and Ausloos (2021) report similar findings in the European market. In their study of EU-domiciled Smart Beta ETFs, "*five out of nine Smart Beta categories outperformed their benchmarks over the sample period*". However, when adjusting for risk, they conclude that "*Smart Beta ETFs fail to achieve greater returns than their passive benchmarks on average.*"

In terms of factor exposure, Blitz (2016) noted that although Smart Beta strategies are generally able to capture specific factors, the degree of exposure they provide to those factors can vary substantially. In many cases, these strategies do not offer maximum exposure to targeted factors. In addition, they retain significant exposure to market index and may exhibit unintended exposures toward other factors. Recent findings by Huang et al. (2024) suggest that newer Smart Beta indices, which are tracked by many recently launched Smart Beta ETFs, often provide weaker exposure to their intended factors compared to the first index created in each factor category. For example, although newer value indices offer slightly stronger exposure to the value factor, newer momentum indices exhibit weaker exposure, with an average beta of 0.290 compared to 0.358 for the first momentum index.

While these studies suggest that Smart Beta ETFs can offer exposure to systematic risk factors, the evidence regarding their ability to consistently deliver superior risk-adjusted returns remains mixed. Although certain categories, such as small-cap strategies, have shown more favourable outcomes in some cases, overall performance has varied across time periods and methodologies. Moreover, comparisons against passive benchmarks often indicate that Smart Beta ETFs do not reliably outperform once risk is accounted for. As such, the empirical support for persistent excess returns remains limited, and further research is needed to better understand the conditions under which these strategies may add value.

4 Data & Methodology

4.1 Portfolio Construction

This thesis examines the performance of Smart Beta ETFs that follow three established factor strategies: size, value, and momentum. The ETF sample was constructed using Morningstar's Screener (2025), focusing exclusively on U.S.-listed equity ETFs that are classified as "Strategic Beta" (Appendix 1), although the classification does not explicitly distinguish size as a separate factor theme. This classification provides a systematic and consistent basis for identifying Smart Beta ETFs, without taking a stance on the exact definition of Smart Beta, which remains debated in academic literature.

The final sample consists of 39 ETFs: 13 for the size strategy, 15 for value, and 11 for momentum (Appendix 2). Only ETFs with continuous return data spanning the full sample period, January 2018 to December 2023, were included. The U.S. market was selected due to its dominance in the smart beta ETF universe, both in terms of product variety and total assets under management (AUM). ETF selection was guided by both factor classification and the goal of achieving factor purity. Only ETFs tilting toward pure factors were included. For the Value strategy, only ETFs categorized by Morningstar (2025) as "Large Value" were included to align with the Fama-French HML factor and ensure focused exposure to the value premium. In the case of the momentum, product availability was more limited, and the sample therefore includes ETFs across small-, mid-, and large-cap segments.

The construction of the Size portfolio presented challenges. Many small-cap Smart Beta ETFs exhibit additional tilts–most often toward value or growth factors. To isolate the size effect and achieve clean exposure to the SMB factor, only ETFs in the "Small Blend" Morningstar category were selected, excluding those with additional tilts. However, many of these ETFs follow traditional market-cap weighting, and the final sample includes both market-cap weighted and alternatively weighted ETFs. Despite this variation in weighting methods, the ETFs are aligned with the broader interpretation of Smart Beta as form of factor investing.

To assess the performance of the selected strategies, equally weighted portfolios were constructed for each factor group. Equal weighting was adopted to enhance diversification and to avoid overrepresentation of the largest ETFs by AUM. This approach ensures that each ETF contributes equally to portfolio performance, which is especially important given the substantial variation in fund size. AUM-weighted portfolios were deemed less suitable for this analysis due to the large dispersion between the smallest and largest ETFs, and due to data availability.

Monthly total return data for each ETF were obtained from LSEG Refinitiv, covering the period from January 2018 to December 2023. Monthly excess returns were calculated by subtracting the risk-free rate from each portfolio's return. The 1-month U.S. Treasury bill rate, sourced from the Kenneth R. French Data Library (2025), serves as the proxy for the risk-free rate. In addition to the Smart Beta portfolios, a benchmark based on a market-cap weighted ETF is included in the analysis. The SPDR S&P 500 ETF (SPY) is used as a passive benchmark for the market, given its widespread use as a benchmark for U.S. equity performance and its popularity among retail investors, which enhances the practical relevance of the analysis. Its excess returns are calculated using the same method as for the Smart Beta portfolios. Benchmark data was also retrieved from LSEG Refinitiv.

To analyse whether the strategies behave differently across market conditions, the full sample period is divided into three sub-periods.

1. January 2018 – December 2019, representing pre-COVID stability,
2. January 2020 – December 2020, capturing heightened volatility during the COVID-19 crisis, and
3. January 2021 – December 2023, reflecting a post-crisis period with shifting macroeconomic conditions.

4.2 Methodology

The risk-adjusted performance of the Smart Beta portfolios is evaluated using time-series regression analysis. Each portfolio and the benchmark are regressed against the Fama-French three-factor model (1993) and the Carhart four-factor model (1997).These models were chosen due to their wide use in empirical asset pricing literature and their ability to capture systematic risk relevant to factor-based strategies.

All factor data were obtained from the Kenneth R. French Data Library (2025). The Fama-French three-factor model includes the market excess return, size (SMB), and value (HML) factors. The Carhart four-factor model extends by adding a momentum factor (UMD). The models are specified as follows:

Fama-French Three-Factor Model (FF3):

$$R_{p,t} - R_{f,t} = \alpha + \beta_i(R_{m,t} - R_{f,t}) + s_i \cdot SMB_t + h_i \cdot HML_t + \varepsilon_{i,t}$$

Carhart Four-Factor Model (CH4):

$$R_{p,t} - R_{f,t} = \alpha + \beta_i(R_{m,t} - R_{f,t}) + s_i \cdot SMB_t + h_i \cdot HML_t + m_i \cdot UMD_t + \varepsilon_{i,t}$$

Where $R_{p,t}$ is the return of the portfolio, the intercept α captures any abnormal return not explained by the included risk factors and the error term $\varepsilon_{i,t}$ represents the portion of returns unexplained by the model. The market, size (SMB), and value (HML) factors aim to capture broad equity risk premia, while the momentum factor (UMD) accounts for return persistence based on past performance.

The regression analysis allows for identifying the portfolios' exposures to the common risk factors and for estimating their risk-adjusted performance through the alpha term. A positive and statistically significant alpha would indicate that the portfolio outperformed expectations on a risk-adjusted basis, meaning it earned returns above what would be predicted by its exposure to common risk factors. Regressions are conducted on portfolio level using the equally weighted mean excess returns of each factor group. All regressions are estimated using ordinary least squares (OLS).

In addition to the regression analysis, this thesis also incorporates two commonly used performance metrics: The Sharpe ratio (Sharpe 1966) and the Sortino ratio (Sortino & Van Der Meer 1991). These measures provide additional insight into return characteristics of each Smart Beta strategy relative to its risk.

The Sharpe ratio measures the average excess return per unit of total risk. It is calculated as the mean of portfolio's excess returns divided by the standard deviation of those returns:

$$Sharpe\ Ratio\ = \frac{E(R_p - R_f)}{\sigma_p}$$

where R_p is the portfolio return, R_f is the risk-free rate, and σ_p is the standard deviation of excess returns. A higher Sharpe ratio indicates a more favourable risk-return trade-off.

The Sortino ratio modifies the Sharpe ratio by replacing total standard deviation with the standard deviation of negative returns (downside deviation):

$$Sortino\ Ratio\ = \frac{E(R_p - R_f)}{\sigma_d}$$

where σ_d denotes the downside deviation of returns that fall below a defined minimum acceptable return, which in this thesis is set to zero.

5 Results

5.1 Descriptive Statistics

Table 1 presents descriptive statistics for the monthly excess returns of the Smart Beta portfolios, along with the market benchmark (SPY), over the full sample period. Portfolio returns were calculated as equally weighted averages of the total monthly returns of the ETFs within each strategy. Excess returns were obtained by subtracting the 1-month U.S. Treasury bill rate from the total returns.

Table 1. Descriptive Statistics of Monthly Excess Returns 2018–2023

Portfolio	Mean Excess Return (%)	Std. Dev. (%)	Min (%)	Max (%)	Obs.
Size	0.680	6.685	-22.271	17.502	72
Value	0.652	5.183	-15.795	13.205	72
Momentum	0.875	5.634	-14.517	12.708	72
Benchmark	0.934	5.204	-12.584	12.691	72

As shown in the table, the benchmark recorded the highest monthly mean excess return over the sample period. On an annualised basis benchmark displays a return of 11.8%, compared to 8.47%, 8.11%, and 11.0% for the Size, Value, and Momentum portfolios, respectively. This indicates that, on average, none of the Smart Beta strategies outperformed the benchmark in terms of excess returns. In addition, each Smart Beta portfolio experienced a more negative minimum return than the benchmark, and only the Value portfolio exhibited a lower return volatility, as measured by standard deviation. However, all Smart Beta portfolios achieved higher maximum monthly returns compared to the benchmark. This suggests that while Smart Beta strategies may not consistently outperform the market, they can generate stronger returns in certain months, likely driven by factor-specific exposures.

The Size portfolio displays the highest standard deviation, along with both the most negative and most positive monthly returns. These findings reflect the trade-offs in factor-based strategies, which may outperform in specific market conditions but also tend to exhibit heightened sensitivity to volatility linked to the targeted factors.

To further illustrate differences over time, Figure 1 presents the cumulative excess returns for each Smart Beta portfolio and the benchmark from January 2018 to December 2023.

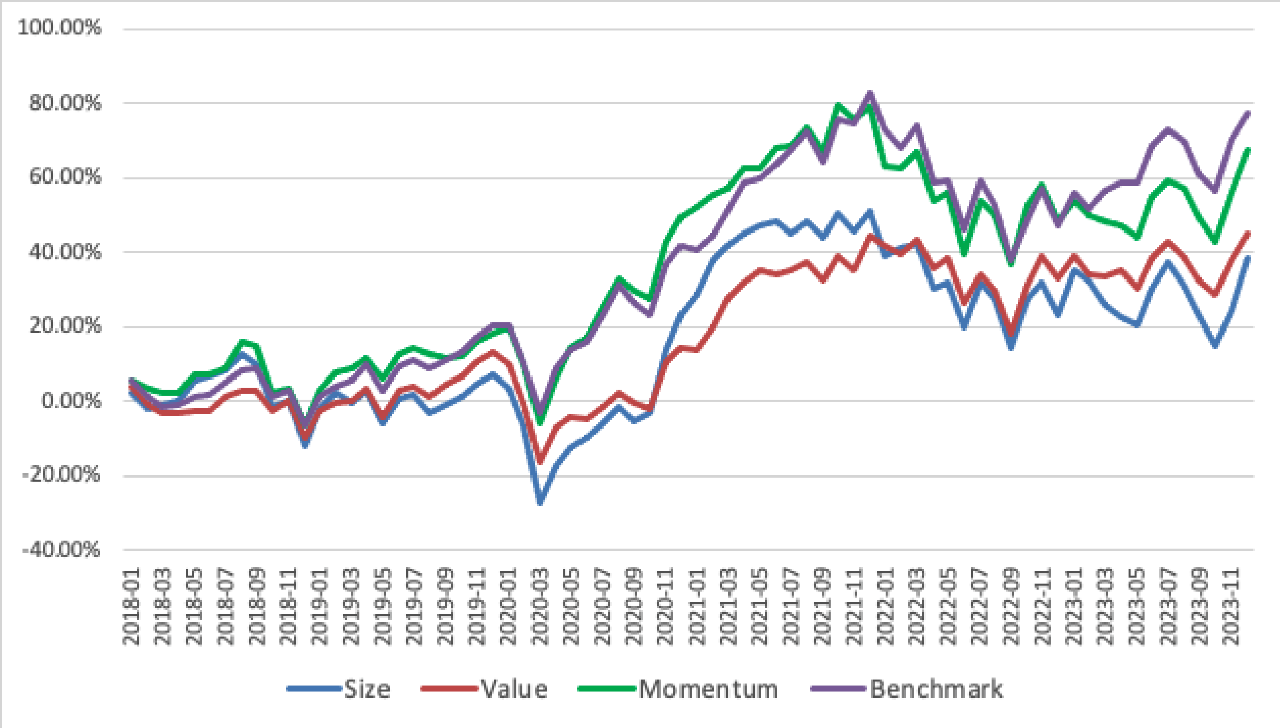

Figure 1. Cumulative returns 2018–2023

Overall, the statistics highlight meaningful differences in the return and risk characteristics of the selected strategies. These patterns will be further examined in the following sections through risk-adjusted performance evaluations using asset pricing models.

5.2 Regression results

Table 2 presents the results of time-series regressions estimated using the Fama-French three-factor model (FF3) and the Carhart four-factor model (CH4) for each Smart Beta portfolio and the market benchmark over the full sample period from January 2018 to December 2023. These models allow for evaluating the portfolios' exposures to systematic risk factors and identifying any abnormal performance through the alpha coefficient. The benchmark serves as a reference point for comparing risk-adjusted performance.

Among the Smart Beta portfolios, the Size strategy displays the most notable exposure to the SMB factor, with coefficients above 0.8 in both models and strong statistical significance. This confirms that the portfolio is tilted toward smaller firms, as intended. The Size portfolio exhibits a market beta close to one, suggesting that its returns move in line with the overall market, despite its strong loading on the SMB factor and higher total volatility. The HML factor is also positive and statistically significant, indicating some overlap with value characteristics despite efforts to isolate the size premium through ETF selection. In contrast, the UMD factor does not show a significant loading in the Carhart model. The alpha is small and statistically insignificant in both regressions, suggesting that the Size portfolio did not generate abnormal returns over the full sample period.

Table 2. Regression results using the Fama-French 3-Factor and Carhart 4-Factor models (2018–2023). Alphas are monthly. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Portfolio	Model	Alpha (%)	Mkt-RF	SMB	HML	UMD	R^2
Size	FF3	0.1	1.008***	0.804***	0.245***	-	0.988
	CH4	0.097	1.008***	0.812***	0.250***	0.021	0.988
Value	FF3	-0.08	0.933***	-0.052	0.347***	-	0.981
	CH4	-0.078	0.927***	-0.059*	0.342***	-0.019	0.981
Momentum	FF3	0.087	0.953***	0.243***	-0.044	-	0.937
	CH4	0.049	1.051***	0.357***	0.038	0.310***	0.976
Benchmark	FF3	0.004	0.990***	-0.175***	-0.004	-	0.998
	CH4	0.004	0.990***	-0.175***	-0.004	0.000	0.998

The Value portfolio shows a strong and statistically significant exposure to the HML factor in both models, confirming that it captures the intended value characteristics. The market beta is slightly below one, which is consistent with the portfolio's focus on value ETFs, as these are often less sensitive to broad market movements. The SMB factor loading is negative, as expected given that all included ETFs focus on large-cap stocks, and the coefficient is not statistically significant. The alpha is negative in both models but lacks statistical significance, suggesting that the Value portfolio slightly underperformed relative to expectations, although not to a meaningful degree.

The Momentum portfolio exhibits a positive and statistically significant loading on the UMD factor in the Carhart model, confirming that it captures the intended momentum exposure. The portfolio also shows a significant positive loading on the SMB factor, which is slightly higher in the Carhart model than in the Fama-French model. The market beta is also higher in the Carhart model (1.051 vs. 0.953), likely due to the absence of the momentum factor in the Fama-French model. The alpha is positive but not statistically different from zero, indicating no abnormal return over the full sample period.

Overall, none of the Smart Beta portfolios produced statistically significant alphas over the full sample period. This suggests that their performance is largely explained by exposures to the established risk factors captured by the models. While the lack of significant alpha indicates that the strategies did not deliver abnormal returns, the factor loadings confirm that each portfolio provided meaningful exposure to its targeted risk premium. All models exhibit high R-squared values (ranging from 0.937 to 0.998), indicating that the used models explain a substantial proportion of variation in monthly excess returns across all portfolios.

5.3 Sub-periods

This section evaluates the performance and factor exposures of the Smart Beta portfolios and the benchmark across three distinct sub-periods: the pre-COVID period (2018–2019), the COVID crisis (2020), and a post-COVID recovery (2021–2023). The aim is to assess how these strategies behave under different market conditions.

Table 3 presents descriptive statistics for the Smart Beta portfolios and the market benchmark during each sub-period. The table reports mean excess returns, standard deviations, and the number of months during which the selected Smart Beta portfolio outperformed the benchmark.

During the pre-COVID period (2018–2019), none of the Smart Beta portfolios outperformed the benchmark on average. Size and Momentum portfolios outperformed in roughly 40% of months, while Value portfolio did so in only 6 out of 24 months (25%).

The COVID crisis year of 2020, marked by extreme volatility, highlighted the strong performance of the Momentum portfolio. It posted the highest mean excess return of 2.27 % and outperformed the benchmark in 10 out of 12 months. Notably, its volatility remained only slightly higher than the benchmark. The Size portfolio also performed well, outperforming the benchmark in 7 out of 12 months, though it exhibited a considerably higher standard deviation. Meanwhile, the Value portfolio continued to underperform, with the lowest return and fewest months of outperformance.

In the post-COVID period (2021–2023), the performance landscape shifted again. The Size portfolio's performance returned to similar levels as before COVID, while the Momentum portfolio continued to outperform the market benchmark in over half of the months (20/36). However, it also experienced the largest decline in mean excess returns, falling to 0.45 %. The Value portfolio produced its strongest results in this period, outperforming the benchmark in 18 out of 36 months and achieving its highest mean excess return across sub-periods. In addition, it also produced the highest mean excess return across all portfolios and the market benchmark. It also had the lowest standard deviation, indicating relatively stable performance.

Table 3. Monthly descriptive Statistics for Sub-Periods

Appendix 3 further presents, on monthly basis, whether each Smart Beta portfolio outperformed the benchmark in terms of mean excess returns.

Portfolio	Period	Mean Excess Return (%)	Std. Dev (%)	Months Outperforming Benchmark (%)
Size	2018–2019	0.434	5.320	9/24 (37.5)
	2020	1.676	10.063	7/12 (58.3)
	2021–2023	0.512	5.980	15/36 (41.7)
Value	2018–2019	0.608	4.142	6/24 (25.0)
	2020	0.400	7.638	3/12 (25.0)
	2021–2023	0.765	4.696	18/36 (50.0)
Momentum	2018–2019	0.812	4.624	10/24 (41.7)
	2020	2.265	7.604	10/12 (83.3)
	2021–2023	0.454	5.314	19/36 (52.8)
Benchmark	2018–2019	0.865	4.112	-
	2020	1.632	7.149	-
	2021–2023	0.746	4.991	-

These findings suggest that while all three Smart Beta portfolios showed demonstrated ability to outperform the benchmark in specific market phases–particularly the Momentum portfolio–performance was not persistent. Furthermore, each portfolio exhibited higher standard deviation than benchmark across all sub-periods, except the Value portfolio during 2021–2023. This shows that Smart Beta strategies are more sensitive to changes in market dynamics, and carry more risk, which is expected, if the additional risk is due to exposure to the desired factor premia.

To gain deeper insight into how the selected Smart Beta strategies performed and factor exposure across different market conditions, separate regression estimates are conducted for each sub-period, and results presented in Table 4.

Table 4. Carhart 4-Factor Regression Results by Sub-Period (2018–2023)

This table reports the results of Carhart four-factor model time-series regressions for each Smart Beta portfolio and the benchmark across three sub-periods: pre-COVID (2018–2019), COVID crisis (2020), and post-COVID recovery (2021–2023). Alphas are monthly. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Portfolio	Period	Alpha (%)	Mkt-RF	SMB	HML	UMD	R^2
Size	2018–2019	0.154	1.018***	0.856***	0.221**	0.003	0.989
	2020	0.399	0.966***	0.678***	0.403***	0.045	0.997
	2021–2023	0.176	1.060***	0.882***	0.261***	-0.001	0.988
Value	2018–2019	0.012	0.966***	-0.168***	0.226***	-0.074	0.989
	2020	-0.387	0.881***	0.002	0.302	-0.057	0.986
	2021–2023	-0.177	0.925***	-0.052	0.353***	-0.004	0.980
Momentum	2018–2019	-0.041	0.992***	0.386***	-0.206**	0.209***	0.984
	2020	0.131	0.983***	0.330	0.028	0.282**	0.991
	2021–2023	-0.029	1.100***	0.372***	0.084**	0.298***	0.971
Benchmark	2018–2019	0.046	0.992***	-0.152***	0.008	0.023*	0.999
	2020	-0.146	0.963***	-0.090*	-0.002	0.030	0.999
	2021–2023	0.011	1.001***	-0.187***	-0.007	-0.006	0.998

The Size portfolio continued to exhibit positive alphas across all sub-periods, with the highest observed during 2020 (0.4%), but none of the values were statistically significant. It continued to show strong loadings on the SMB factor, confirming consistent exposure to the size premium, and also displayed a significant HML loading, suggesting overlap with value characteristics.

The Value portfolio desplayed negative alphas in the two later periods, with the weakest result in 2020 (–0.4%). It exhibits a significant but negative SMB exposure in 2018–2019 and positive HML exposure across all sub-periods, though this loading is insignificant in 2020

The Momentum portfolio produced strong and statistically significant loading to the UMD factor in each sub-period. It also showed positive exposure to SMB and HML in certain sub-periods, reflecting the mixed composition of ETFs used in the portfolio. The alpha was positive in 2020 (0.13%) but not statistically significant, suggesting no abnormal returns even during its strongest performance period.

Overall, the sub-period analysis reinforces the finding that none of the Smart Beta portfolios produced statistically significant abnormal returns, although each strategy maintained consistent exposure to its intended factors. These results also highlight how factor sensitivities shifted modestly across market environments, while the overall explanatory power of the model remained high throughout the sample. Across all sub-periods, the models maintain a R-squared consistently above 97%, reinforcing the robustness of the factor-based approach.

5.4 Sharpe & Sortino Ratios

To complement regression analysis, Sharpe and Sortino ratios were calculated to assess risk-adjusted performance. These metrics provide additional insight by accounting total volatility (Sharpe) and downside risk (Sortino) Results are presented in Table 5.

Table 5. Sharpe and Sortino ratios

	Sharpe				Sortino			
Portfolio	2018–2023	2018–2019	2020	2021–2023	2018–2023	2018–2019	2020	2021–2023
Size	0.35	0.29	0.58	0.30	0.55	0.42	0.76	0.67
Value	0.44	0.51	0.18	0.56	0.67	0.85	0.26	1.15
Momentum	0.54	0.61	1.03	0.30	0.80	0.74	1.51	0.50
Benchmark	0.63	0.73	0.79	0.52	1.04	1.18	1.28	0.96

Over the full sample period, the benchmark outperformed all Smart Beta portfolios on both measures, with a Sharpe ratio of 0.63 and Sortino of 1.04. Among the Smart Beta strategies, Momentum performed best, Sharpe 0.54 and Sortino 0.80, aligning with previous findings.

During pre-COVID period, benchmark outperformed again, while Size strategy lagged on both metrics. 2020 was favourable for Momentum, which achieved the highest Sharpe (1.03) and Sortino (1.51) ratios across all periods. Size also improved while Value underperformed. In the post-COVID period, Value exhibited the highest performed best among strategies, while Momentum's performance weakened, consistent with other results.

Overall, the ratios confirm that none of the Smart Beta portfolios consistently outperform, but Momentum and Value showed notable strenght in specific conditions, while Size underperformed.

6 Conclusions

This thesis examined the performance and factor exposure of three Smart Beta strategies – Size, Value, and Momentum – through equally weighted portfolios constructed using U.S.-listed equity ETFs. The ETF selection was based on Morningstar's "Strategic Beta" classification, and the analysis applied the Fama-French three-factor model and the Carhart four-factor model over the period January 2018 to December 2023. The aim was to evaluate whether these strategies could outperform the market, particularly on a risk-adjusted basis, and to assess their exposure to selected risk factors, and how these changed in different market conditions.

The results display that Smart Beta ETFs demonstrated the ability to outperform the benchmark in terms of mean excess returns during certain sub-periods. However, this outperformance was not persistent and appeared highly sensitive to changing market conditions. Over the full sample period, the benchmark exhibited the highest mean excess return. When risk-adjusted performance was assessed using asset pricing models, none of the Smart Beta portfolios delivered statistically significant alphas across full and sub-periods, suggesting that their returns were largely explained by exposure to risk factors. These results are consistent with Glushkov (2015), who showed that while 60 % of Smart Beta categories outperformed their raw benchmarks, there was no consistent evidence that these strategies delivered greater performance once adjusted for risk. Similar results were shown by Bowes and Ausloos (2021). Glushkov (2015) also noted that only 38% of Smart Beta portfolios produce higher Sharpe and Sortino ratios than their benchmarks, which is in line with the results of this thesis.

Despite the lack of abnormal returns, the regression results indicate that the constructed portfolios effectively captured their targeted factor exposures. The Size portfolio loaded significantly on the SMB factor, the Value portfolio on HML, and the Momentum portfolio on UMD. These results were statistically significant in most sub-periods, confirming effective factor alignment. However, unintended exposures were also observed: the Size portfolio showed a notable loading on HML, and the Momentum portfolio displayed exposure to both SMB and HML. These findings were in line with Glushkov (2015), who found that Smart Beta portfolios tend to load positively on SMB factor, and that they may also exhibit unintended exposures to other factors, which can diminish or counteract the return benefits associated with the intended tilts. Similar results were reported by Blitz (2017), who found that while Smart Beta ETFs commonly exhibit positive exposure to size, value, and momentum factors, the strongest and most consistent loadings are on the size factor. In contrast, value exposures tend to be weaker or diluted, which may reduce the effectiveness of value-focused strategies. All portfolios also exhibited significant exposure to the market factor, which is line with Blitz (2016). This suggests that Smart Beta ETFs, while designed to target specific factors, remain broadly exposed to market risk.

The sub-period analysis showed that factor exposures remained relatively stable across different market conditions, but performance varied considerably. The Momentum portfolio performed best during volatile 2020 period, while the Value portfolio displayed strong results in the post-COVID recovery. Additionally, ratio analysis supported regression results, with the benchmark outperforming the Smart Beta portfolios. However, Momentum and Value strategies demonstrated stronger Sharpe and Sortino ratios in specific sub-periods. Nonetheless, no strategy produced statistically significant alpha in any sub-period, highlighting the dependence of Smart Beta returns on broader market cycles.

Overall, the findings provide limited support for the hypothesis that the selected Smart Beta strategies consistently outperform the market. While they deliver exposure to targeted risk premia, their returns are closely tied to market conditions and fail to generate statistically significant abnormal performance.

This thesis has several limitations that should be acknowledged. First, the definition of Smart Beta varies across index providers, and ETF selection was based solely on to Morningstar's classifications. Although Smart Beta strategies are marketed as transparent and rules-based, index providers retain significant discretion in how these strategies are constructed, which can lead to considerable variation across products. Second, the analysis focused on only three strategies out of the broader universe of Smart Beta strategies, and results cannot be generalized to Smart Beta ETFs as a whole. In addition, the number of ETFs meeting the criteria, particularly in the Size and Momentum categories, was limited, which may affect the generalizability of the findings. Third, the Smart Beta portfolios in this thesis were evaluated against SPDR S&P 500 ETF as a broad U.S. market benchmark. While this enhances practical relevance, it limits the ability to assess performance relative to factor-specific or strategy-related benchmarks. This may affect the interpretation of alphas and limits the ability to evaluate whether Smart Beta ETFs offer better factor exposure relative to their targeted peers. Also, as the regression analysis is conducted using monthly return data, the resulting alphas represent monthly abnormal performance. This should be taken to account when interpreting results.

Future research could expand by including other Smart Beta strategies, such as growth, quality, low-volatility, dividend yield, ESG, or multi-factor combinations. Using more specific, factorrelated benchmarks, could also improve the evaluation of performance and factor exposures within each strategy. In addition, comparisons against actively managed funds and ETFs could offer insight into how Smart Beta ETFs compare relative to active peers targeting similar outcomes. Further studies could also explore Smart Beta in other asset classes beyond equities, such as fixed income and commodities. Finally, extending analysis to markets outside the U.S. may help assess whether Smart Beta strategies behave consistently across different market environments.

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Appendices

Appendix 1 Morningstar Strategic Beta Classification

Strategic Beta Group

The strategic beta group is a classification of the overall strategic beta strategy being employed by the index as a result of its selection and weighting methodology. This attribute helps investors hone in on groups or strategic beta investments with similar objectives.

Also referred to as "smart beta", strategic beta refers broadly to a growing group of indexes and the exchange-traded products and other funds and investment products that track them. The majority of these indexes seek to enhance returns or minimize risk relative to a traditional market-capitalization-weighted benchmark. Others seek to address oft-cited drawbacks of standard benchmarks, such as the negative effect of contango in long-only commodity futures indexes and the overweighting of the most-indebted issuers in market-cap-weighted fixed-income benchmarks.

These benchmarks and the investable products that track them exploit many of the same "factors" (size, value, quality, momentum) in order to mitigate risk in a manner similar to active managers. This group represents a middle ground on the active/passive spectrum, deviating from a traditional strictly passive market portfolio, but doing so in a rules-based, transparent, and relatively low-cost manner.

Appendix 2 ETF Sample

Size Portfolio

ETF Name	Ticker	Fund Size
Vanguard Small-Cap ETF	VB	153 453 520 677
iShares Core S&P Small-Cap ETF	IJR	81 245 768 014
iShares Russell 2000 ETF	IWM	65 004 101 742
Schwab US Small-Cap ETF™	SCHA	16 978 698 760
Vanguard Russell 2000 ETF	VTWO	11 867 323 235
SPDR® Portfolio S&P 600™ Sm Cap ETF	SPSM	11 391 853 004
Schwab Fundamental U.S. Small CompanyETF	FNDA	8 511 051 454
Vanguard S&P Small-Cap 600 ETF	VIOO	4 546 826 083
Invesco FTSE RAFI US 1500 Small-Mid ETF	PRFZ	2 329 099 675
iShares U.S. Small-Cap Eq Fac ETF	SMLF	1 577 875 319
iShares Russell 2500 ETF	SMMD	1 341 917 597
First Trust Small Cap Core AlphaDEX® ETF	FYX	839 179 523
Goldman Sachs ActiveBeta® US SmCp Eq ETF	GSSC	506 231 210

Momentum Portfolio

ETF Name	Ticker	Fund Size
iShares MSCI USA Momentum Factor ETF	MTUM	14 866 468 931
Invesco S&P 500® Momentum ETF	SPMO	5 311 309 148
First Trust Dorsey Wright Focus 5 ETF	FV	3 666 316 703
Invesco S&P MidCap Momentum ETF	XMMO	3 535 718 948
Invesco S&P SmallCap Momentum ETF	XSMO	1 407 273 286
JPMorgan US Momentum Factor ETF	JMOM	1 305 734 153
Invesco Dorsey Wright Momentum ETF	PDP	1 225 155 383
Invesco Dorsey Wright SmallCap Momt ETF	DWAS	677 320 783
Fidelity Momentum Factor ETF	FDMO	551 481 077
SPDR® S&P 1500 Momentum Tilt ETF	MMTM	144 354 168
SPDR® Russell 1000 Momentum Focus ETF	ONEO	87 821 767

Value Portfolio

ETF Name	Ticker	Fund Size
Vanguard Value ETF	VTV	195 238 004 400
iShares Russell 1000 Value ETF	IWD	61 220 944 409
iShares S&P 500 Value ETF	IVE	37 706 379 547
SPDR® Portfolio S&P 500 Value ETF	SPYV	25 432 762 726
iShares Core S&P US Value ETF	IUSV	20 270 041 063
Vanguard Russell 1000 Value ETF	VONV	12 712 046 309
Schwab US Large-Cap Value ETF™	SCHV	12 122 865 802
Vanguard Mega Cap Value ETF	MGV	9 028 613 494
iShares MSCI USA Value Factor ETF	VLUE	7 266 808 307
Vanguard S&P 500 Value ETF	VOOV	5 711 442 268
iShares Russell Top 200 Value ETF	IWX	3 064 150 926
Nuveen ESG Large-Cap Value ETF	NULV	1 668 932 545
Invesco Large Cap Value ETF	PWV	1 033 305 488
iShares Morningstar Value ETF	ILCV	1 000 801 864
Fidelity Value Factor ETF	FVAL	991 660 802

Appendix 3 Whether Smart Beta ETF portfolio outperformed the benchmark in terms of mean excess returns

	Size	Value	Momentum
2018-01	No	No	Yes
2018-02	No	No	Yes
2018-03	Yes	Yes	Yes
2018-04	Yes	No	No
2018-05	Yes	No	Yes
2018-06	Yes	No	No
2018-07	No	Yes	No
2018-08	Yes	No	Yes
2018-09	No	No	No
2018-10	No	Yes	No
2018-11	No	Yes	No
2018-12	No	No	No
2019-01	Yes	No	Yes
2019-02	Yes	No	Yes
2019-03	No	No	No
2019-04	No	No	No
2019-05	No	No	Yes
2019-06	Yes	Yes	No
2019-07	No	No	Yes
2019-08	No	No	Yes
2019-09	Yes	Yes	No
2019-10	No	No	No
2019-11	No	No	No
2019-12	No	No	No
2020-01	No	No	Yes
2020-02	No	No	Yes
2020-03	No	No	No
2020-04	Yes	No	Yes
2020-05	Yes	No	Yes
2020-06	Yes	No	Yes
2020-07	No	No	Yes
2020-08	No	No	No
2020-09	Yes	Yes	Yes
2020-10	Yes	Yes	Yes
2020-11	Yes	Yes	Yes
2020-12	Yes	No	Yes
2021-01	Yes	Yes	Yes
2021-02	Yes	Yes	No
2021-03	No	Yes	No
2021-04	No	No	No
2021-05	Yes	Yes	No
2021-06	No	No	Yes
2021-07	No	No	No
2021-08	No	No	Yes
2021-09	Yes	Yes	Yes
2021-10	No	No	Yes
2021-11	No	No	No
2021-12	No	Yes	No
2022-01	No	Yes	No
2022-02	Yes	Yes	Yes
2022-03	No	No	No
2022-04	Yes	Yes	Yes
2022-05	Yes	Yes	Yes
2022-06	No	No	No
2022-07	Yes	No	Yes
2022-08	Yes	Yes	Yes
2022-09	No	Yes	Yes
2022-10	Yes	Yes	Yes
2022-11	No	Yes	No
2022-12	No	Yes	Yes
2023-01	Yes	No	No
2023-02	Yes	No	Yes
2023-03	No	No	No
2023-04	No	No	No
2023-05	No	No	No
2023-06	Yes	No	Yes
2023-07	Yes	Yes	No
2023-08	No	No	Yes
2023-09	No	Yes	Yes
2023-10	No	No	No
2023-11	No	No	Yes
2023-12	Yes	Yes	Yes