UNIVERSITY OF TURKU
Turku School of Economics

Factor Investing Through Smart Beta ETFs in Europe

Risk-adjusted performance and factor exposure 2017–2025

Department of Accounting and Finance

Bachelor's thesis

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21.4.2026

Turku

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Bachelor's thesis

Subject: Accounting and Finance
Author(s): Matias Eerolainen
Title: Factor Investing Through Smart Beta ETFs in Europe
Supervisor(s): Docent Antti Miihkinen
Number of pages: 39 pages + appendices 1 pages
Date: 21.4.2026

Abstract

Smart beta is often described as an investment methodology that combines attributes of both passive and active investing. Similar to active investment funds, smart beta strategies seek to achieve higher returns relative to broad capital-weighted indices. Unlike active funds, they aim to accomplish this at substantially lower management costs through a rules-based methodology, typically tracking non-capital-weighted indices, which are deliberately structured around well-known fundamental factors such as value, size, volatility, or momentum.

This bachelor's thesis aims to examine the risk-adjusted performance and factor exposure of equity-based smart beta exchange-traded funds (smart beta ETFs) with a targeted allocation to Europe during 2017–2025. The thesis focuses specifically on smart beta ETFs with low-volatility, value, and size factor attributes, forming equal-weighted portfolios for each strategic smart beta group. To assess relative performance, iShares STOXX Europe 600 ETF is used as a practical benchmark representing a broad, capital-weighted ETF in the European stock market. The full sample period is further divided into three distinct sub-periods: 2017–2019, 2020–2022, and 2023–2025. The Smart beta ETF portfolios are evaluated using conventional risk-adjusted performance measures, including the Sharpe ratio, Jensen's alpha, and maximum drawdown as a simple measure of tail risk. The empirical analysis applies the Fama-French three-factor and five-factor models to assess factor exposures to systematic risk factors.

The thesis finds that the selected smart beta categories tend to generate higher absolute returns than the benchmark. Moreover, low-volatility and value smart beta ETF portfolios produce higher returns per unit of risk, as measured by the Sharpe ratio. Nonetheless, this does not extend into statistically significant positive alphas for any of the smart beta ETF portfolios during the sample period. Results from the regression analysis suggest that the value-oriented ETF portfolio captures a clear value premium, while the size-oriented ETF portfolio exhibits a corresponding size premium. At the same time, the low-volatility ETF portfolio exhibits lower sensitivity to market risk and displays positive loading on the CMA factor. The thesis also finds that the size ETF portfolio occasionally produces an overlapping value premium based on the Fama-French three-factor model.

Keywords: risk-adjusted returns, smart beta, factor exposure, ETFs, asset pricing, regression analysis, factor investing

Kandidaatintutkielma

Oppiaine: Laskentatoimi ja rahoitus
Tekijä(t): Matias Eerolainen
Otsikko: Faktorisijoittaminen Smart Beta ETF-rahastojen avulla Euroopassa
Ohjaaja(t): Dosentti Antti Miihkinen
Sivumäärä: 39 sivua + liitteet 1 sivua
Päivämäärä: 21.4.2026

Tiivistelmä

Smart beta kuvataan usein sijoitusmenetelmänä, joka yhdistää ominaisuuksia sekä passiivisesta että aktiivisesta sijoittamisesta. Aktiivisten sijoitusrahastojen tavoin smart beta -strategiat pyrkivät saavuttamaan korkeampia tuottoja suhteessa laajoihin pääomapainotettuihin indekseihin. Toisin kuin aktiiviset rahastot, ne tavoittelevat tätä huomattavasti alhaisemmilla hallinnointikustannuksilla sääntöpohjaisen menetelmän avulla, seuraamalla ei-pääomapainotettuja indeksejä, jotka on tarkoituksellisesti rakennettu tunnettujen fundamentaalisten faktoreiden, kuten arvon, koon, volatiliteetin tai momentumin ympärille.

Tämän kandidaatin tutkielman tavoitteena on tutkia osakepohjaisten smart beta -ETF-rahastojen riskikorjattuja tuottoja ja faktorialtistuksia, jotka kohdennetusti allokoivat Eurooppaan vuosina 2017–2025. Tutkielma keskittyy erityisesti smart beta -ETF-rahastoihin, jotka omaavat matalan volatiliteetin, arvon ja koon faktoriominaisuuksia muodostamalla jokaisen strategian ympärille tasapainotetun portfolion. Suhteellisen tuottosuoriutumisen arvioimiseksi iShares STOXX Europe 600 ETF toimii käytännönläheisenä vertailukohteena, joka edustaa laajaa, pääomapainotettua ETF:ää Euroopan osakemarkkinoilla. Otosjakso on jaettu kolmeen erilliseen alajaksoon: 2017–2019, 2020–2022 ja 2023–2025. Smart beta -ETF-portfolioita arvioidaan perinteisillä riskikorjatuilla tuottomittareilla, kuten Sharpe-luvulla, Jensenin alfalla sekä maximum drawdown -arvoilla yksinkertaisena häntäriskin mittarina. Altistusta systemaattisille riskitekijöille arvioidaan Fama-Frenchin kolme- ja viisifaktorimalleilla.

Tutkielmassa havaitaan, että valitut smart beta -kategoriat tuottavat keskimäärin korkeampia absoluuttisia tuottoja kuin vertailu-ETF. Lisäksi matala volatiliteetti- ja arvo-orientoituneet smart beta -ETF-portfoliot tuottavat korkeampia tuottoja riskiyksikköä kohden Sharpe-luvulla mitattuna. Tämä ei kuitenkaan ulotu tilastollisesti merkitseviksi positiivisiksi alfa-arvoiksi yhdellekään smart beta -ETF-portfoliolle otosjakson aikana. Regressioanalyysi osoittaa, että arvo-orientoituneet smart beta -ETF:t altistuvat selkeälle arvopreemiolle, kun taas koko-orientoituneilla ETF-portfoliolla havaitaan vastaava kokopreemio. Samalla matalan volatiliteetin ETF-portfoliot osoittavat alhaisempaa herkkyyttä markkinariskille sekä positiivisen altistuksen CMA-faktorille. Tulokset osoittavat myös, että kokofaktorin ETF-portfolio tuottaa ajoittain päällekkäisen arvopreemion, etenkin Fama-Frenchin kolmefaktorimallin perusteella.

Avainsanat: riskikorjatut tuotot, smart beta, faktorialtistus, ETF-rahastot, omaisuuserän hinnoittelu, regressioanalyysi, faktorisijoittaminen

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1 Introduction

1.1 Outlook on Europe

Interest in passive asset management has steadily increased over the past decade and currently accounts for approximately 18.2% of all assets under management in Europe. A significant share of this development is linked to the rising popularity of exchange-traded funds or ETFs, largely due to their low-cost structure, high liquidity, and accessibility, as they are traded on secondary markets throughout the day. (EFAMA 2025.) The year 2025 was particularly remarkable from a European perspective. The ETF sector expanded by 41% from the previous year, reaching more than USD 3.2 trillion in assets under management, with projections to surpass USD 6 trillion by the end of 2030 (EY 2026). ETFs have also become an increasingly popular choice among retail investors, as the number of ETF savings plans in Europe rose by 42.1% in 2024. This trend was particularly prominent in France, where ETF purchases among retail investors increased by more than 70% within a single year. (EFAMA 2025.)

Alongside the broader rise of ETFs, so-called smart beta ETFs have also gained increasing attention among both institutional and retail investors in Europe. Although smart beta strategies can be implemented through various investment vehicles, ETFs remain the most dominant alternative (BlackRock 2021). Smart beta represented approximately the fourth-largest individual ETF segment in Europe, with USD 166 billion in assets under management and USD 15.8 billion in net inflows in 2025 (Invesco 2026). Smart beta is often described as an investment methodology that shares traits of passive and active investment funds, given its transparent and rules-based approach, similar to investing in traditional broad capital-weighted indices while simultaneously offering appealing strategic exposure to well-known fundamental factors, resembling more active funds (Mateus et al. 2020). Advocates of smart beta believe that these strategies, which often rely on non-cap-weighted indices, can yield superior returns compared to traditional cap-weighted benchmarks, which they may even refer to as “dumb beta” for holding large amounts of overvalued growth stocks. However, the empirical evidence is more questionable. Generally, smart beta strategies appear to generate higher total returns than their cap-weighted benchmarks, although this involves a higher level of risk. (Glushkov 2015.)

1.2 Research Objectives & Thesis Structure

Although smart beta ETFs have received extensive research, particularly in the United States, less research has concentrated on Europe. To shed more light on the growing market of ETFs, this thesis examines smart beta ETFs with a targeted allocation to Europe, while focusing on three strategic beta groups: low-volatility, value, and size from 2017 to 2025. The aim is to examine smart beta ETFs as a potential alternative to the typical buy-and-hold strategy to capital-weighted market indices by evaluating risk-adjusted returns, factor exposures, and consistency across different market environments. Ultimately, the thesis seeks to determine whether smart beta ETFs offer any meaningful value for investors beyond what traditional passive investment strategies provide in the European context. On this basis, the thesis aims to find answers to the following research questions:

RQ1: *How do European smart beta ETFs perform on a risk-adjusted basis relative to a common European benchmark?*

RQ2: Can European smart beta ETFs produce statistically significant positive Jensen's alpha during the sample period?

RQ3: How do European smart beta ETFs load on different factors based on conventional asset-pricing models?

To address these questions, the research methodology in this thesis is quantitative and relies on the Fama-French three-factor and five-factor models. Relying on both factor models enhances the robustness of the results and allows the identification of potential differences in factor exposures and performance results between the models. The regression results are used to analyse exposure to systematic risk factors, to observe the existence of risk premiums, and deviations in Jensen's alpha over the sample period. In addition, the analysis incorporates the Sharpe ratio to measure relative risk-adjusted performance, as well as maximum drawdown as a simple measure of tail risk.

The thesis is divided into six main chapters: Chapters 2 and 3 begin with the literature review, first outlining the crucial theoretical foundations underlying the empirical section and then extending to the mechanisms behind ETFs and the defining characteristics of smart beta ETFs. Chapter 4 describes choices made regarding the empirical data, detailing where the data was obtained and how it was processed. It also presents the research methodology used for the selected smart beta ETFs, specifying the core decisions made regarding the regression analysis and its limitations, and describing the formulas for measuring relative performance. Chapter 5 begins the empirical analysis by first reporting the cumulative return performance and relative risk-adjusted and downside metrics from the full sample period. The chapter then proceeds to the regression analysis, which evaluates factor exposures and alphas for each smart beta category individually. Chapter 6 concludes by comparing the results with prior academic research, answers the research questions, and draws a concise summary of the observed risk-adjusted results.

2 Asset Pricing

2.1 Modern Portfolio Theory

It is appropriate to begin by highlighting the importance of modern portfolio theory, as it forms the basis for all conventional asset pricing models. Harry Markowitz published his journal article *Portfolio Selection* in the Journal of Finance in 1952, regarding the rational way to construct an investment portfolio. The key premise of modern portfolio theory is the E-V rule, in which a risk-averse investor evaluates an investment solely based on its expected return and its risk, i.e., volatility of an asset measured by variance (σ^2) or standard deviation (σ). Under the E-V rule, the investor aims either to maximize a portfolio's expected return at a constant risk level or to minimize risk at a constant expected return. The E-V rule emphasizes the importance of diversifying a portfolio across assets with low covariance, in practice across different industries that behave differently through business cycles.

Markowitz (1952) introduced the concept of efficient frontier to characterize the set of portfolios that are optimal by the E-V rule. The efficient frontier is represented as a curve traced out from the portfolio's weights of chosen assets (Figure 1). When a portfolio lies on the efficient frontier, there is no other combination of asset weights that can offer an equal or higher expected return with a lower variance, nor a lower variance for the same expected return. Therefore, portfolios on the efficient frontier represent the best attainable trade-offs between risk and return.

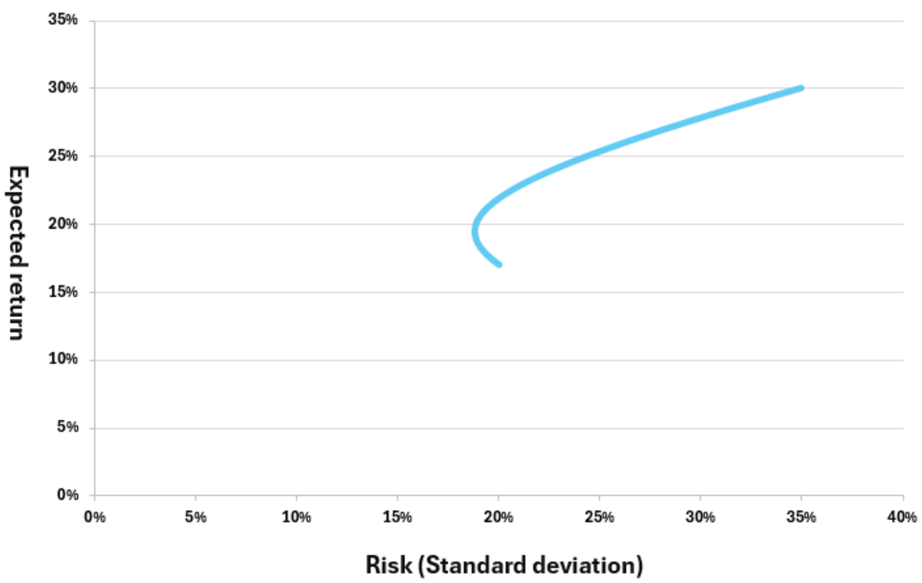

Figure 1 Illustration of the efficient frontier of two risky assets

2.2 Capital Asset Pricing Model

The Capital Asset Pricing Model (CAPM) is the first and most well-known asset pricing model. The formula for CAPM was introduced by William F. Sharpe in 1964 and John Lintner in 1965. However, crucial preliminary work for CAPM was also made by James Tobin in 1958, who linked the concept of a risk-free asset to Markowitz's modern portfolio theory. When a risk-free asset is included, a capital market line can be formed. The capital market line presents all efficient combinations of a risk-free rate and a risky portfolio, i.e., a tangent portfolio that dominates the efficient frontier presented by Markowitz. (Sharpe 1964.) In the CAPM formula, the tangent portfolio equals the market portfolio, a theoretical portfolio consisting of all available assets in proportion to their market size.

The Capital Asset Pricing Model can be expressed as follows:

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

$E(R_i)$ equals the expected return for an asset i, which consists of the asset-specific risk premium and risk-free rate. The beta coefficient β_i measures how sensitive the return of an asset is to movements in the market portfolio, therefore expressing its level of systematic risk. Systematic risk refers to a portion of total risk that comes from volatility in the market portfolio that cannot be eliminated by diversification. If beta is greater than 1, it indicates that the asset tends to be more volatile than the market portfolio, while a beta less than 1 indicates that the asset is less volatile. $E(R_m)$ signifies the expected return of the market portfolio, while R_f is the return of a risk-free asset, thus $E(R_m) - R_f$ provides the risk premium over the risk-free asset for bearing market risk.

Despite the theoretically sound foundation of the CAPM, it has also faced criticism, especially concerning its empirical applicability. Roll (1977) criticized the concept of market portfolio, which, in theory, should include all marketable assets across all asset classes. In practice, the market portfolio is often approximated using a relatively limited set of assets, such as the S&P 500 index, which consists of 500 publicly traded large-cap companies in the U.S. stock market. However, these proxies are approximations of the theoretical market portfolio, and this inevitably leads to inaccuracies in the estimates produced by the CAPM.

The introduction of the CAPM made it possible to empirically measure the risk-adjusted performance of an asset on an absolute basis. Jensen (1968) refined the CAPM framework by incorporating an additional constant term to capture variation in realized returns unexplained by the

CAPM's predictions. This term is generally referred to as Jensen's alpha (α), which provides a measure of risk-adjusted performance relative to known risk factors. In this way, an investor can identify the presence of excess or abnormal returns and compare risk-adjusted performance across different assets and investment strategies.

The CAPM formula with Jensen's alpha can be defined as follows:

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

$R_i - R_f$ implies the realized return R_i for an asset i over the risk-free rate R_f, while alpha α_i captures excess return that is unexplained by exposure to market risk. Jensen (1968) noted that a positive alpha can exist under two circumstances: 1) the investor or fund manager can generate returns exceeding those implied by risk-adjusted expectations, or 2) negative bias from estimated beta inflates the alpha estimate. Thus, correctly specifying the market portfolio and the risk-free rate is essential for objectively assessing risk-adjusted performance using Jensen's alpha.

2.3 Efficient Market Hypothesis

Eugene Fama published a journal article, *Efficient Capital Markets: A Review of Theory and Empirical Work*, in The Journal of Finance in 1970. The article introduced a remarkable hypothesis at the time about market efficiency and its various levels. At the core of the Efficient Market Hypothesis (EMH) remains the idea that a security price fully reflects all available information. When markets fully reflect all information, all investing strategies based solely on this information cannot be used to achieve excess returns over time.

According to Fama (1970), security markets can be divided into three categories depending on the level of their market efficiency:

Weak form refers to market efficiency in which past price information cannot be used to predict future price movements. In such markets, past and future price changes are independent. This idea is often described as a random walk, referring to the way prices appear to wander unpredictably over time. However, the weak form does not rule out the possibility that other types of information could be used to earn excess returns.

Semi-strong form means that neither past price information nor publicly available information can be used to achieve excess returns. Public information includes, for example, stock splits, earnings announcements, annual reports, and other publicly accessible information. When the semi-strong form prevails, markets will react immediately to new public information to adjust prices accordingly.

Strong form implies that all available information, whether price-related, public, or private, is immediately reflected in security prices. This would mean that even market participants with potential access to monopolistic information, such as institutional investors or market makers, could not earn excess returns over the long term.

Fama's (1970) empirical results provided compelling evidence for weak and semi-strong forms of efficiency in financial markets. However, Fama noted that the strong form of market efficiency is more debatable, although empirical findings of the performance of institutional funds appeared to support it.

2.4 Anomalies in Efficient Markets

The empirical work of the EMH has faced conflicting evidence since its initial release. One piece of evidence against markets fully reflecting all available information is often associated with market anomalies. A market anomaly can be described as a systematic pattern in returns that cannot be explained by the predictions of a given asset pricing model. These anomalies can be interpreted as market inefficiency or, alternatively, failure of the chosen asset pricing model to include all underlying risk factors. (Malkiel 2003.) This thesis will next present a few well-known and persistent market anomalies that later become important in the empirical part of this thesis.

2.4.1 Low volatility

Initial findings of a mismatch between systematic beta risk and returns predicted by the CAPM were already noted by Haugen and Heins in 1972. Their empirical analysis indicated that more volatile stock portfolios did not consistently offer a higher risk premium as traditionally expected by the CAPM formula. Instead, stock portfolios composed of low-volatility or low-variance stocks earned higher risk-adjusted returns than their more volatile counterparts from 1926 to 1971 in the New York Stock Exchange (NYSE).

A more contemporary perspective was provided by Blitz and Pim van Vliet in 2007, who examined the low-volatility effect across the US, Japanese, and European equity markets between 1986 and 2006. Their empirical evidence confirmed its persistence across all three regions. Statistically significant positive alphas were observed with both the CAPM and Fama-French three-factor model. The research also found that in Europe, risk-adjusted measures such as the Sharpe ratio, which evaluates returns per unit of risk, low-volatility stocks appeared to perform particularly well relative to their higher-volatility counterparts. Correspondingly, evidence for distinct underperformance of stock with high idiosyncratic risk, i.e., high firm-specific volatility, has been documented in a global context by Ang et al. (2009) across G7 countries. In this regard, the low-volatility effect appears to be a universal phenomenon, not overly restricted by regional differences in equity markets.

2.4.2 Value

The idea that value stocks could systematically outperform the market dates to the 1930s and was introduced in Benjamin Graham's and David Dodd's renowned investing book, *Security Analysis,* in 1934. The book introduced the underpinnings of value investing, in which stocks that appear underpriced based on fundamental analysis are expected to appreciate towards their intrinsic value over time.

Perhaps the first academic journal article empirically examining the value anomaly was published by Sanjoy Basu in 1977. Basu demonstrated that firms with low price-to-earnings (P/E) ratios on the NYSE earned abnormal returns that could not be fully explained by the CAPM's market risk factor or beta. The lowest two deciles of P/E-sorted portfolios consistently outperformed randomly selected portfolios with equivalent risk levels. Basu interpreted these findings as evidence that stock prices did not fully incorporate all publicly available information about earnings, contrary to the semi-strong form of the EMH. Supportive evidence for value anomaly has also been presented by Rosenberg et al. (1985), who documented a positive relationship in the cross-sectional returns of stocks sorted by book-to-market (B/M) ratio in the U.S. equity markets.

2.4.3 Size

In 1981, Rolf Banz found that stocks with small market capitalization appeared to outperform their large-capitalization counterparts on the NYSE between 1926 and 1975. His empirical framework extended the CAPM formula by including the market value of an equity as an additional factor. Partly due to Roll's (1977) critique of the unobservability of the true market portfolio, Banz employed three different market indices as proxies for the market portfolio. Banz then demonstrated that firms with low market value earned risk-adjusted excess returns relative to their beta-equivalent firms with high market value. Banz argued that this was evidence of misspecification of the CAPM, and size may act as a reliable proxy for unknown risk factors. There has been supporting evidence of the size anomaly across Europe, Asia, and several emerging markets in the past. However, it should also be noted that the existence and reliability of the size effect have been questioned in recent decades. (Van Dijk 2011.)

2.5 Fama-French Factor Models

Fama-French factor models are multifactor asset pricing models that aim to explain asset returns by incorporating multiple risk factors rather than relying on a single market factor. The development of more advanced factor models was driven by extensive empirical evidence of market anomalies, which challenged the capability of the CAPM framework to reliably account for observed return patterns. In particular, Ross's (1976) Arbitrage Pricing Theory (APT) paved the way for multi-factor models, stating that returns are driven by a number of systematic risk factors. Although APT itself does not specify which factors should be taken into account, it served as a crucial foundation for the development of more advanced asset pricing models.

Fama and French (1992) provided comprehensive evidence that the Sharpe-Lintner CAPM fails to explain average stock returns when relying solely on its single market factor. Fama and French formed portfolios into deciles by market size (stock price times shares outstanding) and book-to-market ratio (B/M) of stock data from the NYSE. Their evidence showed a negative relationship between size and average returns and a strong positive relationship between book-to-market ratio and average returns. These findings supported earlier observations of the size anomaly by Banz (1981) and the value anomaly by Basu (1977) and Rosenberg et al. (1985). Fama and French argued that if asset pricing is rational, market size and book-to-market ratio should serve as reliable proxies for common risk factors in returns (Fama and French 1992). In 1993, Fama and French introduced two additional risk factors: the size factor (SMB) and the value factor (HML). Alongside the market factor, these formed the Fama-French three-factor model, offering a more convincing explanation of stock returns (Fama and French 1993).

The Fama-French three-factor model can be expressed as follows:

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

In the three-factor model, $R_i - R_f$ equals the realized excess return over the risk-free rate R_f for an asset i. The alpha α_i captures the abnormal return while the beta β_i measures sensitivity to market risk. $E(R_m)$ indicates the expected return of the market portfolio, therefore, $E(R_m) - R_f$ refers to the market risk premium. The s_i coefficient captures the exposure to the size factor, while h_i captures exposure to the value factor. HML (High Minus Low) is the average return of high B/M ratio stock portfolios minus the average return of low B/M ratio stock portfolios. Similarly, SMB (Small Minus Big) is the average return of small-cap stock portfolios minus the average return of large-cap stock portfolios.

Fama and French later extended their three-factor model to address some of its weaknesses. The primary acknowledged flaw of the three-factor model was its inability to account for differences in firms' profitability and investment behavior affecting average returns. Past empirical evidence has documented a profitability premium, where firms with higher operating profitability tend to generate higher returns than unprofitable firms, and an investment premium, where firms that invest aggressively tend to earn lower returns than their conservative counterparts. From this basis, the Fama-French five-factor model incorporates the profitability factor (RMW) and investment factor (CMA), alongside the original market, value, and size factors. Fama and French also acknowledged one notable limitation of the five-factor model. The five-factor model often overpredicts returns of small firms that invest heavily despite weak profitability. (Fama and French 2015.)

The Fama-French five-factor model can be expressed with the following formula:

$$R_i - R_f = \alpha_i + \beta_i\left[E(R_m) - R_f\right] + s_i SMB + h_i HML + r_i RMW + c_i CMA$$

In the Fama-French five-factor model, the r_i coefficient captures the sensitivity of a security or portfolio to the profitability factor, whereas c_i captures its sensitivity to the investment factor. The RMW (Robust Minus Weak) term is calculated as the difference in returns between diversified stock portfolios of firms with high and low operating profitability. The CMA (Conservative Minus Aggressive) term is calculated as the difference in returns between diversified stock portfolios of low-investment firms and high-investment firms, which are often referred to as conservative and aggressive.

3 Smart Beta ETFs

3.1 Exchange-traded Funds

Exchange-traded funds (ETFs) are a relatively new investment vehicle in financial markets, as the first ETFs were introduced in the early 1990s. The oldest ETF still in operation is the SPDR by State Street, launched in 1993, which initially tracked only the S&P 500 index. Since then, the ETF market has expanded substantially, offering a broad spectrum of products, including fixed-income, commodity, currency, actively managed, as well as thematic ETFs such as smart beta. (Lettau and Madhavan 2018.) According to the Investment Company Institute's (ICI) 2024 annual report, the ETF industry currently holds over USD 10 trillion in net assets in the United States, making it the largest and most developed ETF market globally. In Europe, the sector remains significantly smaller but continues to grow, with EUR 2.1 trillion in net assets in 2024 (EFAMA 2025).

Exchange-traded funds typically share hybrid traits of common stocks and traditional mutual funds. They consist of pooled assets from which investors can purchase shares, but as their name indicates, ETFs are exchange-traded on secondary markets throughout the day, like common stocks. This structure makes ETFs readily accessible through online trading platforms and allows a wider range of investors to participate in the market with relatively small initial capital. (Hill et al. 2015.) Although there are actively managed ETFs, the vast majority of ETFs track specific market indices without an active portfolio manager, which consequently reduces management costs (Lettau and Madhavan 2018). For instance, the average annual expense ratio for actively managed ETFs was approximately 0.44%, whereas expenses for index-tracking ETFs were only 0.14% in 2024 (ICI 2024).

Unlike common stocks, ETF shares are created through a specific process consisting of transactions between Authorized Participants (APs) and ETF’s fund managers (Figure 2). Authorized Participants are typically large broker-dealers or market-makers who are authorized to buy and deliver a basket of desired securities from capital markets to the ETF fund manager. An ETF fund manager offers, in exchange, newly created ETF shares, known as “creation units,” valued at the Net Asset Value (NAV). Net Asset Value refers to the net value of securities under the ETF fund divided by the number of ETF shares outstanding. APs can sell the acquired ETF shares on the secondary market to investors. Similarly, APs can redeem ETF shares by returning them to the fund manager in exchange for the underlying securities or cash at NAV, therefore reducing the number of ETF shares circulating in the secondary market. This cycle of creation and redemption also supports market liquidity by providing arbitrage opportunities for APs when investors have an excess buying or selling demand for ETFs. (Hill et al. 2015.) (Madhavan 2014.) Moreover, the redemption mechanism allows ETF fund managers to control their holdings without generating taxable capital gains in the process, as they can exchange underlying securities “in-kind” rather than selling them to raise excess cash for redemptions (Poterba and Shoven 2002).

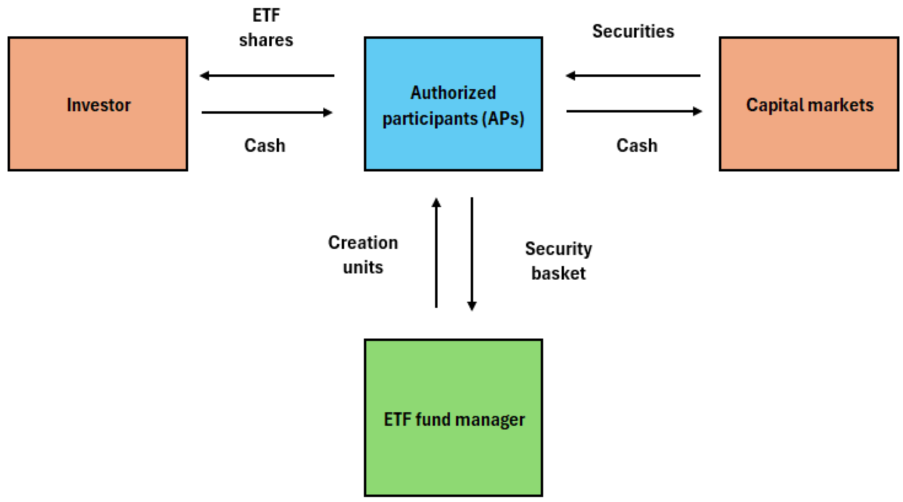

Figure 2 Simplified illustration of ETF architecture

Adapted from Lettau and Madhavan 2018

3.2 Smart Beta ETFs

As discussed in Chapter 2, previous research has documented several persistent market anomalies that have often been interpreted as evidence against the CAPM framework or as objections against the theory of efficient markets. Some of these persistent market anomalies were incorporated into factor models, where they are treated as systematic risk factors to explain return observations (Appendix 1). These empirical findings have eventually led to factor investing. Through factor investing, investors seek exposure to fundamental factors in exchange for earning a higher risk premium (Bender et al. 2013). For example, an investor aiming to capture the value premium may intentionally construct a portfolio of stocks with relatively high book-to-market value in hopes of achieving greater returns.

Until recently, factor investing was mainly accessible through actively managed investment funds, which inevitably led to higher management fees (Bender et al. 2013). In contrast, smart beta seeks to outperform traditional market capitalization-weighted indices by tilting portfolio holdings towards specific factors in a rules-based manner, without relying on active portfolio management. Instead of using broad capital-weighted indices, smart beta aims to use alternative weighting methods or non-capital weighting methods that may place more emphasis on certain factor attributes. (Hsu et al. 2012.) Smart beta ETFs usually implement this by tracking indices designed to target factors, such as the MSCI Europe Value Index, which consists of European stocks exhibiting value-related characteristics (MSCI 2026). Smart beta strategies' transparency in factor implementation and the mechanical index-based methodology generally result in lower total costs for investors when compared with actively managed funds (Hsu et al. 2012).

Although smart beta can be perceived as combining the best bits of passive and active investing, implementing these strategies in practice is far from straightforward. As investment decisions in smart beta strategies are typically made at the outset through a rules-based methodology rather than dynamically throughout the investment process, a continuously evolving market environment can hinder the effectiveness of exposure to the targeted factors. A transparent investment strategy that relies on widely known factor attributes and publicly available information also creates additional vulnerabilities, such as strategy overcrowding or front-running. Overcrowding refers to a phenomenon in which a large number of investors buy or sell the same securities based on similar factor attributes, potentially leading to overvaluation or sharp price crashes. Front-running occurs when investors anticipate and trade ahead of the smart beta fund's rebalancing trades, which typically occur at fixed quarterly or even annual intervals, thereby eroding the return performance of smart beta funds. (Jacobs and Levy 2014.) (Jacobs and Levy 2015.)

One of the first academic studies assessing the performance of smart beta ETFs is Glushkov's (2015) comprehensive study of ETFs in the U.S. markets, which finds that more than 60% of smart beta ETFs outperform their declared benchmarks in terms of total returns, although risk-adjusted outperformance is generally uncommon. Hence, risk-adjusted returns or alphas tend to be close to zero. Although smart beta ETFs typically exhibit the intended exposure to their target factors, the results also indicate that these products may not deliver perfectly isolated factor tilts and instead often display secondary exposures alongside their primary factor (Glushkov 2015). Blitz (2019) presents similar conclusions, noting that smart beta indices may suffer from factor overlap, which can undesirably erode the targeted risk premium. Nevertheless, smart beta ETFs should not be viewed as an exceptional source of positive alpha or superior risk-adjusted performance, but rather as a convenient and cost-effective way of obtaining systematic exposure to desired factors.

4 Empirical Data and Methodology

4.1 Description of the Selected ETFs

The empirical section of this thesis aims to evaluate the performance of smart beta ETFs in Europe during 2017–2025. The main objective is to gain a broader perspective on how smart beta ETFs have performed and implemented their core strategy in the European stock market during the sample period. Smart beta ETFs have received considerably less academic attention in Europe than in the United States. The availability of smart beta ETFs in European equity markets is still relatively limited across various strategic beta groups, which likely contributes to the smaller number of published studies. For this reason, the empirical analysis focuses on size, value, and low-volatility strategies, as these smart beta categories contain perhaps the largest number of individual smart beta ETFs allocating to Europe and therefore provide a more representative sample for analysis. The sample period from 2017 to 2025 was selected to balance sufficient ETF availability for analysis with a long enough time horizon to meaningfully assess the performance of smart beta ETFs in the European context.

All ETF funds were screened using common screening platforms, such as the Morningstar ETF Screener, JustETF.com, and LSEG Workspace, as well as artificial intelligence. ETFs were then evaluated with a particular emphasis on their smart beta characteristics, fund size, inception date, and allocation. This assessment relied on information provided in the Key Information Document (KID), as well as the fund's overall description on the platform. Some of the selected ETFs also incorporate ESG and dividend-related criteria into their investment strategies. This means that the ETF does not rely only on its primary factor exposure. The growing importance of ESG seems to play a major role also in smart beta ETFs, as these funds aim to appeal to more responsible investors. These ETFs were still included in the analysis to increase the sample size, as these additional characteristics do not prevent the funds from implementing their primary smart beta strategy and are likely to increase the explanatory power of the results.

The initial goal was to select a minimum of 5 ETFs for each smart beta category. Ultimately, 21 smart beta ETFs were selected: 8 representing the size factor, 7 for the value factor, and 6 for the low-volatility factor (Figure 3). For all selected ETFs, monthly adjusted price and return data for the full sample period were sourced from LSEG Workspace. Adjusted price data were used to eliminate distortions caused by dividends, splits, or other actions that do not reflect actual return performance.

To assess relative performance, BlackRock's iShares STOXX Europe 600 ETF was chosen as the benchmark. This ETF represents approximately the 600 largest publicly traded companies in Europe and is constructed using a capital-weighted methodology. From an investor's perspective, this benchmark should serve as a practical reference point for the average return on European stock markets for ETFs.

Benchmark

Name	Ticker	Fund size	TER p.a.	Inception Date
iShares STOXX Europe 600	EXSA	$ 9400M	0.20 %	2004

Low volatility

Name	Ticker	Fund size	TER p.a.	Inception Date
iShares Edge MSCI Europe Minimum Volatility	EUN0	$ 832M	0.25 %	2012
Invesco EURO STOXX High Dividend Low Volatility	EHDV	$ 414M	0.30 %	2016
Amundi MSCI Europe Minimum Volatility Factor	MIVA	$ 158M	0.23 %	2009
BNP Paribas Easy Low Volatility Europe	VLEU	$ 66M	0.31 %	2016
State Street SPDR EURO STOXX Low Volatility	ZPRL	$ 33M	0.30 %	2014
UBS Factor MSCI EMU Low Volatility	UIMY	$ 9M	0.30 %	2015

Value

Name	Ticker	Fund size	TER p.a.	Inception Date
iShares Edge MSCI Europe Value Factor	CEMS	$ 2500M	0.25 %	2015
UBS MSCI EMU Value	EMVEUA	$ 356M	0.30 %	2009
Xtrackers MSCI Europe Value	D5BL	$ 231M	0.15 %	2010
State Street SPDR MSCI Europe Value	ZPRW	$ 62M	0.20 %	2015
UBS Factor MSCI EMU Prime Value Screened	UIMZ	$ 61M	0.30 %	2015
Deka STOXX Europe Strong Value 20	EL4D	$ 55M	0.70 %	2008
BNP Paribas Easy Value Europe	VALU	$ 49M	0.31 %	2016

Size

Name	Ticker	Fund size	TER p.a.	Inception Date
Xtrackers MSCI Europe Small Cap	XXSC	$ 2900M	0.30 %	2008
iShares MSCI EMU Small Cap	SXRJ	$ 900M	0.58 %	2009
UBS MSCI EMU Small Cap	ESCEUA	$ 647M	0.30 %	2011
iShares STOXX Europe Small 200	EXSE	$ 548M	0.22 %	2005
iShares EURO STOXX Small	IQQS	$ 399M	0.40 %	2004
State Street SPDR MSCI Europe Small Cap	SMC	$ 276M	0.30 %	2014
BNP Paribas MSCI Europe Small Caps SRI PAB	EESM	$ 219M	0.25 %	2016
WisdomTree Europe Small Cap Dividend	WTES	$ 45M	0.38 %	2014

Figure 3 Selected ETFs for analysis

4.2 Research Methodology & Limitations

The framework for empirical research partly resembles the methodology used by Glushkov (2015) but focuses specifically on smart beta ETFs with an allocation to European equity markets. The regression analysis is conducted using both the Fama-French three-factor and five-factor models. Relying on both models can increase the robustness of the results while also providing a comparison of how the models may differ in explaining returns. Monthly European factor returns for both models were retrieved from Kenneth French's data library. The risk-free rate used in the regression analysis is the 1-month U.S. Treasury bill, also directly sourced from Kenneth French's data library.

To further assess relative risk-adjusted performance and downside risk, the Sharpe ratio and maximum drawdown are used in the empirical section. The Sharpe ratio was originally introduced by William F. Sharpe in 1966 to evaluate the risk-adjusted returns of an asset. The Sharpe ratio measures the excess return over the risk-free rate relative to the unit of total risk taken. As discussed earlier, risk is typically measured by the standard deviation of an asset's returns. Thus, the Sharpe ratio can be expressed with the following formula:

$$Sharpe\ ratio = \frac{R_p - R_f}{\sigma_p}$$

R_p tells the realized return of the portfolio p, hence the expression $R_p - R_f$ provides the portfolio's excess return over the risk-free rate R_f and σ_p is the standard deviation. A high Sharpe ratio is often desired, as it indicates that an investor earns a greater return relative to the risk tolerated. The Sharpe ratio is typically measured on an annual basis.

Maximum drawdown signifies the worst possible drop in an asset's value during the time series under analysis, indicating how much an investor could have lost when the value falls from peak to trough (Gray and Vogel 2013). Maximum drawdown can be expressed with the following equation:

$$Maximum\ drawdown\ (MDD) = \min_{\forall t,T}\left(\prod_{t}^{T} r_{i,t} - 1\right)$$

In the equation, r is the return of an asset i at time t, the point at which the asset reaches its peak value within the period under analysis. Similarly, T refers to the point at which the asset reaches its trough value. The expression considers all possible time intervals within the period under analysis and identifies the exact peak-to-trough interval that results in the lowest cumulative return percentage.

The research methodology also introduces a few limitations that should be acknowledged. Because the analysis includes only smart beta ETFs that remained active throughout the entire sample period, any ETFs that were liquidated during the sample period are excluded. This creates a risk of survivor bias, as the sample may reflect only those ETFs that performed exceptionally well during the sample period. The sample also does not account for transaction costs or management fees, which may vary across individual smart beta ETFs, as seen in Figure 3. However, these costs are typically relatively small and are unlikely to drastically affect the results obtained. The risk-free rate used in this thesis, the U.S. 1-month Treasury bill, does not perfectly reflect the average risk-free rate in the euro zone. Although considerations were made to convert all factor returns into euros and conduct the analysis entirely in a euro-based framework, the U.S. risk-free rate was ultimately chosen because both the factor returns and the corresponding risk-free rate obtained from Kenneth French's data library are primarily constructed in U.S. dollars. This choice also offers a more straightforward comparison with results from U.S. equity markets. It should also be noted that the selected benchmark is neither the declared benchmark nor the reported parent index for each selected smart beta ETF. For simplicity, the selected benchmark was used as a single common benchmark for each constructed smart beta ETF portfolio.

5 Empirical Results

5.1 Overview

The empirical section first presents overall return performance metrics from the full sample period and the sub-periods across all observed portfolios. Figure 4 illustrates the cumulative returns over the full sample period (2017–2025). In terms of total returns, the value portfolio shows the highest overall return by the end of 2025, reaching 106.83%. The gap between the value portfolio and the other portfolios is notable. The low-volatility portfolio generates 82.41%, the benchmark 81.20%, and the size portfolio 81.19% by the end of 2025. Overall, the performance of the benchmark does not stand out from the smart beta portfolios in terms of total returns. This observation is still consistent with previous findings from U.S. ETF markets, for instance, Glushkov (2015) reports that approximately 60% of smart beta categories outperformed their declared benchmarks in terms of total returns. Return performance in general appears lower than in U.S. equity markets, where rapid growth is strongly driven by high-tech firms. In Europe, market performance is typically affected by more conservative sectors such as industrials or banking, which tend to generate steadier but slower returns over time.

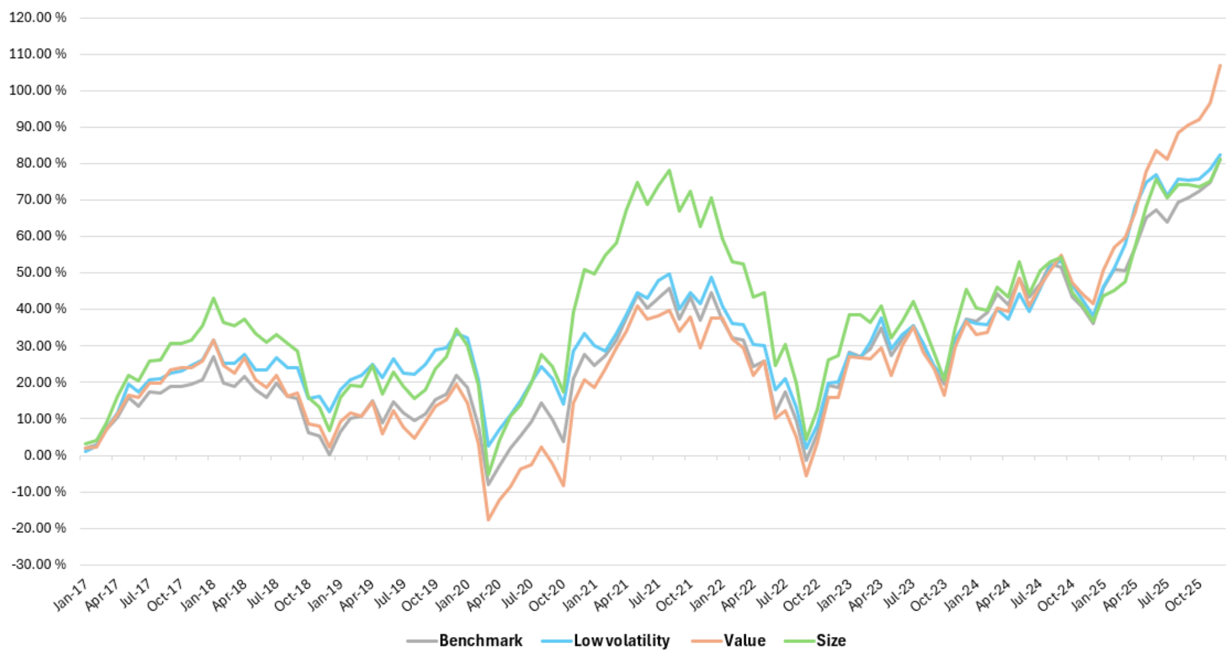

Figure 4 Cumulative returns 2017–2025

The low-volatility portfolio slightly outperforms the benchmark for most of the sample period in terms of cumulative returns (Figure 4). In addition, it overall delivers higher risk-adjusted performance than the benchmark, as indicated by its Sharpe ratio of 0.37 over the full sample period

(Table 1). The only notable exception occurs during the second sub-period (2020–2022), where the low-volatility portfolio is the only portfolio to present a negative Sharpe ratio at -0.10, potentially indicating weaker risk-adjusted performance during broad market downturns such as the COVID-19 crisis or at the beginning of the war in Ukraine. As expected, its standard deviation remains the lowest among all portfolios across each sample period. Less volatile behaviour is also supported by the maximum drawdown percentages, which consistently present smaller price drops during periods of market turmoil than those of the other smart beta portfolios or the benchmark.

In terms of cumulative returns, the value portfolio remains mostly below the benchmark until it begins a steep growth at the start of 2025 (Figure 4). This steep growth curve is also reflected in its risk-adjusted metrics, as the value portfolio records the highest Sharpe ratio of 1.04 in the last sub-period (Table 1). From a risk-adjusted basis, the value portfolio performs well relative to the benchmark, as can be observed by its highest overall Sharpe ratio from the full sample period at 0.39. The maximum drawdown percentages indicate larger price declines relative to the benchmark and the low volatility portfolio, which can generally be expected from tilting portfolio holdings toward riskier value-oriented firms. Overall, the second sub-period was marked by significant downside risk based on maximum drawdown values, especially due to the global pandemic and the war in Ukraine.

The size portfolio outperforms the benchmark in terms of cumulative returns for most of the sample period (Figure 4). Regarding this, one striking observation is its strong performance in the aftermath of the COVID-19 crisis, as the size portfolio rose by more than 50% between March 2020 and March 2021. Despite this, it exhibits the lowest Sharpe ratio over the full sample period at 0.32 (Table 1). The size portfolio tends to generate weaker risk-adjusted returns than the benchmark, and it consistently displays the highest drawdown percentages in each sample period. Similarly, its standard deviation tends to remain highest in each sample period, indicating more sensitivity to large shifts in the European equity market.

Table 1 Risk-adjusted metrics from the full sample period

Both the mean excess return over the risk-free rate and the standard deviation are measured as monthly averages.

Period	Portfolio	Mean excess return	Standard deviation	Sharpe ratio	Max drawdown
2017–2025	Benchmark	0.475%	4.802%	0.34	-32.26%
	Low volatility	0.461%	4.334%	0.37	-31.83%
	Value	0.640%	5.619%	0.39	-37.51%
	Size	0.524%	5.717%	0.32	-40.48%
2017–2019	Benchmark	0.479%	3.459%	0.48	-21.23%
	Low volatility	0.717%	2.994%	0.83	-14.87%
	Value	0.441%	3.854%	0.40	-22.33%
	Size	0.779%	4.110%	0.66	-25.48%
2020–2022	Benchmark	0.087%	6.588%	0.05	-32.26%
	Low volatility	-0.172%	5.829%	-0.10	-31.83%
	Value	0.158%	7.856%	0.07	-37.51%
	Size	0.101%	7.825%	0.04	-40.48%
2023–2025	Benchmark	0.860%	3.852%	0.77	-18.07%
	Low volatility	0.838%	3.720%	0.78	-18.75%
	Value	1.321%	4.382%	1.04	-17.41%
	Size	0.693%	4.638%	0.52	-32.22%

5.2 Results From the Factor Models

The regression results for both factor models are described in more detail for each smart beta portfolio in separate subsections. Table 2 reports the estimated factor returns for the Fama-French three-factor model, and Table 3 reports the equivalent results for the Fama-French five-factor model. From a general perspective, none of the portfolios exhibit statistically significant positive alphas (Table 2, Table 3). From this basis, it can be stated that neither the smart beta portfolios nor the benchmark could generate risk-adjusted returns reliably exceeding overall expectations during any of the sample periods. Despite this, the low-volatility portfolio displays positive alphas under both factor models during the first sub-period (2017–2019), although the magnitude is negligible. The explanatory power of the regressions appears convincing across both models, as indicated by the adjusted coefficient of determination (Adj. R^2). The additional RMW and CMA factors in the five-factor model appear to only marginally increase the explanatory power of the results, indicating that the three-factor model already absorbs most of the return variation through its parameters. The last sub-period (2023–2025) generally shows the weakest explanatory power, although the difference remains marginal. Similarly, both factor models tend to explain less of the variation in returns of the low-volatility portfolio. This is perhaps due to its limited exposure to specific risk factors such as SMB and HML, as most of its variation is captured by the beta. In addition, the low-volatility portfolio contains the smallest number of individual smart beta ETFs, which may contribute to its relatively lower explanatory power.

5.2.1 Low-volatility portfolio

As mentioned, the low-volatility portfolio exhibits positive alphas under both factor models, particularly during the first sub-period (Table 2, Table 3). However, these estimates are not statistically significant, and therefore, no reliable conclusions can be drawn about the existence of positive abnormal returns. Moreover, this positive pattern is almost nonexistent, corresponding to only 0.03–0.04% monthly outperformance relative to the factor models' predictions.

Secondly, the low-volatility portfolio consistently displays the lowest statistically significant betas across the full sample and within each sub-period (Table 2, Table 3). This outcome meets expectations, as it indicates that the low-volatility portfolio is less sensitive to market risk and therefore carries less systematic risk than the other smart beta portfolios or the benchmark. This relatively small sensitivity to market risk is also consistent with the risk-adjusted performance metrics in Table 1, where both the standard deviation and maximum drawdown values were generally lower. From this basis, it can be concluded that the low-volatility portfolio implements its core strategy as desired.

The SMB factor remains statistically insignificant across all sample periods and fluctuates between positive and negative values, indicating that the low-volatility portfolio does not provide distinct and reliable exposure to returns of either small-cap or large-cap firms during the sample period. The HML factor is negative and statistically significant only from the full sample period and under the five-factor model (Table 3). This suggests a slight tilt toward firms with typical quality or growth characteristics, although this pattern is not persistent or statistically significant across each sub-period.

Under the more comprehensive five-factor model, the low-volatility portfolio also exhibits statistically significant and positive exposure to the CMA factor in both the full sample period and the last sub-period (Table 3). In addition, the CMA loading remains consistently positive across all sample periods. Altogether, this observation suggests that the low-volatility strategy tends to lean more toward conservative firms with relatively low capital expenditures, which aligns well with its defensive strategy. Although RMW loading is mostly positive, it is statistically significant only in the second sub-period, indicating temporary exposure to firms of relatively high profitability. From a broader perspective, it remains difficult to draw consistent conclusions about the loadings for the RMW factor.

5.2.2 Value portfolio

The value portfolio exhibits negative and statistically significant alphas, particularly over the full sample period and the first sub-period under both factor models (Table 2, Table 3). This points to an extremely small, but longer-term, underperformance relative to the return expectations of the factor models. In contrast to the low-volatility portfolio, the beta of the value portfolio remains consistently above 1, implying greater sensitivity to market risk than the European equity market on average.

The HML factor stays positive and statistically significant across all sample periods and under both models (Table 2, Table 3). This discrete and robust observation provides convincing evidence that the value portfolio successfully captures the intended value premium. Similar to the low-volatility portfolio, the SMB factor fluctuates between positive and negative values and remains statistically insignificant, indicating no meaningful or consistent secondary factor premium to SMB.

A notable finding from the five-factor model is the positive and statistically significant RMW factor loading during the first sub-period, suggesting that the value portfolio tilts more toward firms with both value and profitability characteristics between 2017 and 2019 (Table 3). However, the pattern is short-lived and does not continue in other sample periods. Overall, the value portfolio mainly appears to show a clear focus on its core value strategy.

5.2.3 Size portfolio

The size portfolio exhibits a negative and statistically significant alpha throughout all sample periods, indicating a slight underperformance under both factor models, which is similar to the findings for the value portfolio (Table 2, Table 3). Its beta is typically the highest among all portfolios across each sample period, indicating a higher magnitude of systematic risk. This outcome is also in line with the risk-adjusted metrics in Table 1, where the size portfolio often displays the highest standard deviations, as well as the highest drawdown values during major market downturns. The size portfolio likely includes more illiquid firms that may still be in the early stages of their business development, which generally leads to more volatile market behaviour.

The results from both factor models provide strong evidence of a distinct size premium for the size portfolio (Table 2, Table 3). The SMB factor remains positive and statistically significant across all sample periods, indicating that the size portfolio consistently tilts toward small-cap firms. In this respect, the size portfolio successfully captures the size premium, providing a clear tilt toward small-cap firms as intended.

Moreover, the size portfolio also occasionally exhibits positive and statistically significant exposure to the HML factor, particularly under the three-factor model (Table 2). Under the five-factor model, the HML remains positive but not statistically significant, suggesting that the additional RMW and CMA factors may absorb part of this loading from the HML (Table 3). However, the explanatory power of the regression analysis increases only marginally with the inclusion of these additional factors, and neither RMW nor CMA shows reliable and persistent statistical significance over the whole sample period. From this basis, the size portfolio appears to exhibit a slight value premium alongside the preliminary size premium during the sample period.

Table 2 Regression results from the Fama-French three-factor model

This table reports factor returns of the Fama-French three-factor model, incorporating three factors: Beta, SMB, and HML to explain the cross-sectional variation in monthly returns in each sample period under analysis. All returns are in decimal format. Significance levels: *** p < 0.001, ** p < 0.01, * p < 0.05

Period	Portfolio	Alpha	Beta	SMB	HML	Adj. R^2
2017–2025	Benchmark	-0.003***	1.002***	-0.092**	0.008	0.989
	Low volatility	-0.002	0.877***	-0.074	-0.025	0.926
	Value	-0.003**	1.092***	0.017	0.440***	0.980
	Size	-0.002**	1.103***	0.613***	0.099***	0.984
2017–2019	Benchmark	-0.003***	0.986***	-0.094	-0.043	0.978
	Low volatility	0.0003	0.826***	-0.204	-0.052	0.906
	Value	-0.003*	1.054***	-0.143	0.359***	0.964
	Size	-0.001	1.133***	0.481***	-0.054	0.974
2020–2022	Benchmark	-0.002**	1.010***	-0.091*	0.005	0.995
	Low volatility	-0.004*	0.885***	-0.088	-0.045	0.958
	Value	-0.003	1.094***	0.003	0.453***	0.987
	Size	-0.003*	1.078***	0.644***	0.105***	0.992
2023–2025	Benchmark	-0.002	0.996***	-0.108	0.031	0.978
	Low volatility	-0.001	0.908***	0.009	0.053	0.859
	Value	-0.002	1.121***	0.142	0.399***	0.969
	Size	-0.004*	1.150***	0.653***	0.215***	0.976

Table 3 Regression results from the Fama-French five-factor model

This table reports factor returns of the Fama-French five-factor model, incorporating five factors: Beta, SMB, HML, RMW, and CMA to explain the cross-sectional variation in monthly returns in each sample period under analysis. All returns are in decimal format. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Period	Portfolio	Alpha	Beta	SMB	HML	RMW	CMA	Adj. R^2
2017–2025	Benchmark	-0.002***	1.005***	-0.086**	0.002	0.014	0.046	0.989
	Low volatility	-0.001	0.917***	0.014	-0.169*	0.159	0.488***	0.935
	Value	-0.003**	1.089***	0.014	0.440***	-0.033	-0.032	0.979
	Size	-0.002**	1.101***	0.625***	0.062	0.021	-0.010	0.984
2017–2019	Benchmark	-0.003**	0.990***	-0.101	-0.081	-0.029	0.056	0.977
	Low volatility	0.0004	0.828***	-0.153	-0.032	0.266	0.300	0.905
	Value	-0.003**	1.036***	-0.062	0.609***	0.564***	0.139	0.975
	Size	-0.002	1.117***	0.500***	0.123	0.184	-0.209	0.975
2020–2022	Benchmark	-0.002*	1.015***	-0.073	-0.006	0.040	0.077	0.995
	Low volatility	-0.005*	0.873***	0.009	0.044	0.486*	0.246	0.966
	Value	-0.003	1.084***	-0.024	0.489***	-0.052	-0.126	0.987
	Size	-0.004**	1.054***	0.668***	0.158	0.212	-0.049	0.993
2023–2025	Benchmark	-0.002	0.997***	-0.123	0.019	-0.052	0.035	0.976
	Low volatility	-0.002	0.969***	-0.011	-0.206	-0.108	0.683**	0.895
	Value	-0.002	1.111***	0.083	0.326***	-0.233	0.004	0.970
	Size	-0.004*	1.140***	0.602***	0.094	-0.238*	-0.021	0.977

6 Conclusions

The purpose of this thesis was to examine risk-adjusted performance and factor exposure of smart beta ETFs with a targeted allocation to Europe during 2017–2025. This objective was organized around three research questions introduced in Chapter 1. To capture potential time-series variation in performance, the full sample period was further divided into three sub-periods. The quantitative methodology relied on the Fama-French three-factor and five-factor models, as well as risk-adjusted performance and downside risk measures such as the Sharpe ratio and maximum drawdown. The empirical sample consisted of 21 European smart beta ETFs across three categories: low-volatility, value, and size, which were organized into separate smart beta ETF portfolios. For relative comparison, BlackRock's iShares STOXX Europe 600 ETF served as a benchmark, representing the average return available for investors through a broad, capital-weighted European equity ETF.

Based on the results obtained, Sharpe ratios appear higher for the value and low-volatility categories, whereas the size portfolio remains slightly below the benchmark in the full sample period. Based purely on Sharpe ratios, the value and low-volatility portfolios therefore appear to have provided better returns relative to total risk taken than the benchmark during the full sample period. Prior academic research by Thomann and Safoschnik (2019) provides supportive evidence for European smart beta indices between 2001 and 2018. Their results present that value, size, and momentum factor indices outperformed their declared benchmark indices based on the Sharpe ratio. These findings together provide supportive evidence that especially value-oriented smart beta strategies have potentially outperformed broad cap-weighted indices in terms of the Sharpe ratio over a long period in Europe. Similar to the results of this thesis, Thomann and Safoschnik (2019) report relatively higher maximum drawdown percentages for European value and size factor indices, revealing a greater price decline in market crises. Jensens' alphas estimated with the three-factor and five-factor models indicate that none of the smart beta categories or the benchmark generated positive statistically significant alphas during the sample period, implying no superior risk-adjusted performance relative to the returns explained by the factor models. Although the low-volatility portfolio produced marginally positive alphas (0.03%–0.04%) in the first sub-period (2017–2019) under both factor models, no reliable conclusions can be drawn at the 5% significance level.

The low-volatility portfolio exhibits the lowest exposure to market factor, with its beta remaining consistently below 1, which is expected. Over the full sample period and in the last sub-period, the CMA factor is positive and statistically significant, indicating a tilt toward more conservative or low-investing firms, which aligns well with the defensive nature typically associated with low-volatility strategies. The value portfolio shows a positive and significant HML loading under both factor models, confirming the presence of a value premium among the selected smart beta ETFs. The size portfolio in turn displays a consistently positive and statistically significant SMB loading across both models and all sample periods, providing evidence of a systematic size premium within the selected small-cap smart beta ETFs. Interestingly, the size portfolio also exhibits an occasional value premium alongside its primary size tilt, particularly under the three-factor model. While this result was not initially expected, smart beta strategies have been found to offer exposure to additional factors alongside their primary factor exposure, as previously discussed in Chapter 3.

In conclusion, the risk-adjusted evidence from the observed sample suggests that low-volatility and value smart beta ETFs have generated marginally higher returns relative to total risk than the chosen cap-weighted benchmark ETF in the European context on average over the nine-year sample period. However, this outperformance does not imply that these smart beta strategies generated returns exceeding overall expectations or achieved superior risk-adjusted performance beyond what the applied factor models would predict.

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Appendices

Appendix 1 Common systematic factors

Systematic Factors	What It is	Commonly Captured by
Value	➢ Captures excess returns to stocks that have low prices relative to their fundamental value	➢ Book to price, earnings to price, book value, sales, earnings, cash earnings, net profit, dividends, cash flow
Low Size (Small Cap)	➢ Captures excess returns of smaller firms (by market capitalization) relative to their larger counterparts	➢ Market capitalization (full or free float)
Momentum	➢ Reflects excess returns to stocks with stronger past performance	➢ Relative returns (3-mth, 6-mth, 12-mth, sometimes with last 1 mth excluded), historical alpha
Low Volatility	➢ Captures excess returns to stocks with lower than average volatility, beta, and/or idiosyncratic risk	➢ Standard deviation (1-yr, 2-yrs, 3-yrs), Downside standard deviation, standard deviation of idiosyncratic returns, Beta
Dividend Yield	➢ Captures excess returns to stocks that have higher-than-average dividend yields	➢ Dividend yield
Quality	➢ Captures excess returns to stocks that are characterized by low debt, stable earnings growth, and other "quality" metrics	➢ ROE, earnings stability, dividend growth stability, strength of balance sheet, financial leverage, accounting policies, strength of management, accruals, cash flows

Retrieved from Bender et al. 2013

Appendix 2 Explanation of the use of AI

AI-based tools, such as Gemini, Grammarly, and Copilot, were used to assist with the grammatical accuracy and structure in this thesis. It was also utilized to filter and suggest ETFs for portfolio construction and provide ideas for academic sources.