Smart Beta ETFs Under Stress

Cross-Regional Factor Loadings and Performance During COVID-19 and the Russia-Ukraine War

AALBORG UNIVERSITET

Master Thesis by

Till Röckle (20231423)
M.Sc. Finance

Submitted to:
Caglar Kaya
Aalborg University Business School
Fibigerstræde 2 | 9220 Aalborg | Denmark
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Abstract

This thesis explores how Smart Beta exchange-traded funds (ETFs) behaved during two significant recent periods of financial distress: the COVID-19 pandemic and the Russia-Ukraine conflict. Drawing on return data from over 200 ETFs based in the US and Europe, the study examines how exposure to established risk factors, such as momentum, value, size, and profitability, shifted during these crisis episodes. The empirical analysis proceeds in two stages. First, panel regressions incorporating the Carhart 4-factor model and extended six-factor model assess how sensitivities to key financial factors evolved during periods of market disruption. Next, the performance of smart beta strategies is evaluated using risk-adjusted (rolling) metrics, including the Sharpe, Sortino, and Information ratios. The results suggest of this analysis that factor exposures are not static, but rather respond to changes in market conditions, with the momentum and value factors showing especially marked variation under stress. Additionally, ETFs domiciled in Europe exhibited greater fluctuations in exposure than their US counterparts. While smart beta strategies do not consistently outperform their benchmarks, multifactor approaches appear to offer more stable outcomes. This research adds to the growing body of literature on factor-based investing by providing empirical evidence on how Smart Beta ETFs adapt under real-world financial stress.

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1 Introduction

Exchange-traded funds (ETFs) have grown from niche into mainstream investment products over the past two decades. Global ETF assets reached over $11 trillion by 2023, reflecting investors broad adoption of passive, index-linked strategies (State Street Global Advisors, 2024). Within this expansion, Smart Beta ETFs, also known as strategic or factor-based ETFs, have emerged as a fast-growing segment. These Smart Beta funds differ from traditional market-capitalization weighting by tilting toward factors such as value, momentum, quality, low volatility, or size stocks. The appeal is to combine the low-cost, transparent indexing of ETFs with factor exposures that academic research has linked to long-term excess returns (Le, 2023). This academic foundation has fueled the rapid rise of factor-oriented ETFs in the 2010s. Smart Beta ETFs have consequently captured a significant share of the overall ETF market. In the US, Smart Beta equity ETFs grew to about 22% of total US ETF assets by the end of 2019. Global assets in Smart Beta ETFs stood at roughly $835 billion in late 2019, reflecting a five-year compound annual growth rate near 20% (ETFGI, 2019). That growth continued despite market disruptions, and by early 2024 Smart Beta ETF assets worldwide had roughly doubled to $1.56 trillion (ETFGI, 2024). This represents roughly 15-20% of equity ETF assets globally, underscoring that smart beta has moved from a niche to a mainstream strategy. The trend is especially pronounced in the US, where investors have readily embraced factor ETFs as alternatives to both active mutual funds and pure market-index funds. Large institutional investors (e.g. pension plans like CalPERS and Norways sovereign fund) have also incorporated multifactor benchmarks, lending further credibility to factor-based approaches (Ang, 2014). By contrast, Europes ETF market has seen a more gradual adoption of smart beta. European domiciled strategic-beta ETPs accounted for only about 57% of the regions ETF assets as of 2022 (Silano, 2023), totaling roughly $100 billion in AUM. Growth in Europe has been steady but slower, in part because traditional index products and newer thematic or ESG ETFs have attracted more attention. Nonetheless, European interest in factors is rising, and surveys indicate a growing number of investors plan to increase allocations to smart beta strategies. Both in the US and Europe, the appeal of amart beta lies in its promise: delivering better beta, meaning enhanced return or reduced risk relative to capitalization-weighted indexes, while retaining liquidity, transparency, and low fees. In practice, Smart Beta ETFs have drawn investors by offering systematic factor exposures at much lower cost than traditional active funds. For example, research shows smart beta ETFs in the U.S. have offered higher factor-driven returns at lower fees than many closet index active mutual funds, prompting investors to replace high-cost active funds with factor ETFs (J.P. Morgan Asset Management, 2024). This migration underscores how Smart Beta products blur the line between active and passive investing, effectively democratizing quantitative factor strategies that were once the domain of active managers. As a result of recent events, the global markets in 2025 are navigating a complex interplay of macroeconomic, geopolitical, and technological factors. Inflation and fluctuating interest rates have created uncertainty for investors. Furthermore, escalating geopolitical tensions, notably the ongoing Russia-Ukraine conflict and renewed US-China trade disputes, display a critical uncertainty for investors across the globe. As of April 2025, global ETFs reached a record in assets under management of \$15.44 trillion, with smart beta strategies accounting for a big portion of this growth (ETFGI, 2025). Just in Europe, the ETF market is projected to reach \$4.5 trillion by 2030, driven by an increase in retail adoption and product innovation (McIlvenna et al., 2025). This development shows the investors' desire for cost-effective and rules-based investment solutions that can potentially outperform traditional benchmarks. Despite their systematic approach, Smart Beta ETFs are not free of market volatility, especially during periods of financial stress. The COVID-19 pandemic and the Russia-Ukraine war have tested the robustness of these factor-based strategies. Research indicates that factor exposures can shift significantly during crises, potentially undermining the diversification benefits these strategies are designed to provide.

The motivation behind this thesis is based on the increasing significance of Smart Beta ETFs in global capital markets and the growing investor focus on factor-based strategies for cost-effective and diversified portfolio construction. As Smart Beta ETFs continue to blur the line between passive and active management, understanding their behavior during times of financial stress becomes critically important, both academically and practically. The years 2019 to 2025 have provided a rare sequence of distinct market shocks, including the COVID-19 crash, inflation-driven bear markets, and banking sector turmoil, offering a valuable natural experiment to assess how different factor exposures perform under extreme conditions. This thesis aims to analyze the robustness and resilience of factor loadings in Smart Beta ETFs during such crises. The findings will inform whether these products deliver on their promise of better beta precisely when investors need it most and contribute to the broader discourse on factor investings effectiveness in real-world, high-stress environments.

1.1 Problem Statement and Research Objective

While factor investing and Smart Beta ETFs are well studied, less attention has been paid to how factor exposures behave during financial crises. Existing research typically focuses on long-term performance or individual factors in isolation. Few studies examine how real-time factor exposures shift under market stress, particularly when comparing Europe and the US. This thesis addresses that gap by examining how ETF sensitivities to common risk factors evolve during financial crises, with a focus on whether the momentum (WML) factor becomes more dominant in stressed markets. This analysis uses interaction terms to capture structural breaks in time, such as the transition from the pre-crisis to the crisis period. It compares European and US Smart Beta ETFs to examine whether their factor exposures change across these periods and whether such shifts are linked to more stable or more volatile performance outcomes.

Research Question

How do factor exposures affect the return and risk characteristics of European and US Smart Beta ETFs during periods of financial crisis and elevated market uncertainty?

Hypothesis

H1: The momentum factor (WML) exhibits a dominant and increasing influence on Smart Beta ETF returns during periods of financial crisis and elevated market uncertainty.

H2: European Smart Beta ETFs exhibit significantly more pronounced and volatile shifts in factor exposures compared to US-based ETFs during periods of market stress.

H3: Smart Beta ETFs do consistently outperform either their respective factor benchmarks or broad market indices on a risk-adjusted basis, particularly during and following periods of financial crisis.

The thesis contributes to the existing literature on Smart Beta ETF investing by providing an empirical analysis of factor exposures and the performance characteristics of Smart Beta ETFs across the US and the EU. While most of the existing research has focused on US markets, this study extends the scope by also including European Smart Beta ETFs, a relatively underexplored region, thereby offering new empirical evidence on their behavior during recent market crises. Furthermore, the thesis addresses the ongoing debate, whether Smart Beta ETFs really outperformance their benchmarks. By connecting factor exposures to actual performance measurements, it provides a critical perspective on the theoretical advantages of smart beta strategies and their practical implementation. In doing so, it fills a regional and temporal research gap and deepens our understanding of the structural constraints that can prevent academic and theoretical factor models from consistently delivering outperformance in the real world.

In order to fill this gap, this paper uses a two-stage empirical framework to evaluate the behavior and performance of Smart Beta ETFs across US and European markets. The first stage focuses on the analysis of factor exposures and loadings, while the second stage assesses the risk-adjusted performance across different market regimes. In the exposure analysis, a comprehensive panel of over 200 Smart Beta ETFs is examined across four major categories (value, momentum, low volatility, and multifactor) in both US and EU markets. To determine whether these ETFs show the expected sensitivities to systematic risk factors, factor regressions are conducted using two model specifications. First, the Carhart four-factor model is applied to capture standard style tilts. Second, an extended six-factor model further includes profitability and investment factors, offering a broader perspective on factor alignment. In order to evaluate the stability of these factor exposures under stress situations, a panel regression framework is used that interacts crisis-period dummy variables with the factor loadings. This approach allows for the estimation of factor loadings, enabling an analysis of the time-varying sensitivities of Smart Beta ETFs.

The following paper is organized as follows. Chapter 2 provides a literature review, positioning smart beta within the broader evolution of asset management and exploring its theoretical foundations alongside key empirical discussions. Chapter 3 outlines the data sources, describes the construction of the used performance metrics, and details the methodological framework used to estimate factor loadings during the predefined crisis periods. Chapter 4 presents the core empirical results, including an analysis of factor exposures as well as the relative performance of smart beta portfolios against their respective benchmarks. Chapter 5 analyzes these empirical findings within the broader academic debate, bringing in comparisons with recent studies. It also critically evaluates the limitations of the research. Practical implications for investors are considered. The final chapter summarizes the main insights derived from the analysis and evaluates the findings in relation to the stated hypotheses. In addition, it outlines the studys contribution to the existing academic literature on smart beta investing.

2 Theoretical Framework

2.1 Beyond CAPM: Factor Models

Early asset pricing theories suggested that a single market factor would drive the expected returns, as formalized by the Capital Asset Pricing Model (Sharpe, 1964). The theory of CAPM and the Efficient Market Hypothesis (EMH) states that all publicly available information is fully reflected in market prices (Fama, 1970). This implies that investors cannot consistently generate risk-adjusted excess returns above those offered by a market capitalization-weighted index. However, since the 1980s, extensive research has questioned and explored this view by highlighting market anomalies and identifying risk factors that connect specific stock characteristics to higher returns in the long term. (Banz, 1981) was one of the first to demonstrate the size effect, thereby showing that small-cap stocks tend to outperform large-cap stocks. This finding suggested that firm size, not captured by the CAPM, plays a significant role in explaining returns. (Fama & French, 1993) extended these findings by developing a three-factor model, known as the Fama-French three-factor model, that incorporates both size and value factors. They found that value stocks, defined by high book-to-market ratios, consistently outperform growth stocks, thereby improving the explanatory power of asset pricing models. (Jegadeesh & Titman, 1993) later found a momentum effect that shows that stocks with strong recent returns continue to outperform in the short term. These discoveries led to the formulation of multifactor models, such as the Fama-French five-factor and six-factor extensions, which introduced profitability and investment patterns as additional determinants of expected returns. The models tried to better explain asset prices by recognizing that more than one type of factor affects returns. Academic research has found that these factors help to explain why some stocks perform better than others. (Asness et al., 2013) demonstrated that value and momentum are persistent across asset classes and regions, confirming their robustness in the market. (Hou et al., 2015) then provided strong evidence for the size effect, documenting that small firms deliver higher returns because of less information efficiency and higher risk exposure. Low volatility strategies also challenge traditional finance assumptions. (Ang et al., 2006) showed that stocks with low idiosyncratic volatility tend to generate higher returns, while (D. C. Blitz & van Vliet, 2007) documented the so-called low volatility anomaly, where low-risk stocks outperform high-risk stocks. Furthermore, (Chen, 2009) found that firms with high and sustainable dividend yields tend to deliver better future returns, suggesting that dividends signal financial strength and stability. (Fama & French, 2015; Novy-Marx, 2013) emphasized the role of "quality," defined through profitability and conservative investment strategies, as a key predictor of long-term performance. Despite the empirical support for these factors, some researchers have raised concerns about the long-term reliability of these factors. (McLean & Pontiff, 2016) examined the performance of factor strategies after they have been published and found that their returns tend to weaken after becoming widely known, suggesting overfitting or market adaptation issues. (Arnott et al., 2021) warns that the effectiveness of factor strategies can decrease over time because of arbitrage activity and investor crowding, especially since they are implemented on larger scales.

2.2 ETF Investment Strategies

2.2.1 Active vs. Passive Investing

Unlike traditional active management, which is heavily dependent on manager discretion, passive investing represents an investment strategy that tries to track and imitate a market-weighted index or portfolio. (Arnott et al., 2005) proposed fundamental indexation, which shows that weighting portfolios by fundamentals, such as book value or earnings, leads to outperformance compared to indices that are weighted by market capitalization. (Wermers, 2000) showed that while some active managers possess skill, the average mutual fund fails to outperform its benchmark (net of fees), pointing out the challenge of consistent alpha generation through active stock selection. This finding is consistent with broader empirical evidence. For example, the SPIVA U.S. Year-End 2021 report shows that a majority of actively managed equity funds consistently underperform their benchmarks (Liu & Sinha, 2022). (Elton et al., 1996) confirmed that mutual funds show persistent underperformance after fees, while (Fama & French, 2010) found that most fund outperformance relates to luck rather than skill. (Malkiel, 1995) similarly observed that the higher costs because of active management weaken performance advantages relative to passive strategies that are cheaper in price. Furthermore, (Ang et al., 2009) evaluated the active management of Norways sovereign wealth fund, concluding that rule-based strategies which target specific factors could improve performance. However, not all research dismisses the value of active management. (Cremers & Petajisto, 2009) introduced the concept of Active Share and found that funds with high Active Share and long-term investment horizons tend to outperform their benchmarks. (Hunter et al., 2014) highlighted the value of Active Peer Benchmarks in better identifying skilled fund managers who consistently produce positive alpha, while (Cremers et al., 2019) argued that the widespread skepticism about active management may be overstated, providing evidence that certain fund managers deliver persistent value to investors. Adding further to this debate, (Berk & van Binsbergen, 2015) argues that while most mutual fund managers do not outperform on average, the alpha produced by skilled managers may be absorbed by fees. This means that the skill of managers may not translate into higher returns for investors because it is balanced out by fees and costs. Their findings suggest that investing decisions made by investors respond to manager skill, even if the net returns appear low. Moreover, (Nicolas & Busse, 2005) explored short-term performance persistence and found that mutual funds showing strong performance over very short horizons (one to three months) tend to outperform in the near future. Although the effect fades quickly, it raises questions about how persistent active management value really is. On the passive side, (D. Blitz & Swinkels, 2008) provides evidence that alternative index construction methods, including fundamental and equal weighting, can outperform traditional capitalization-weighted indices. This supports the view that structured, rules-based strategies can outperform without relying on active stock selection.

In conclusion, academic research presents a mixed view: Although active management tends to underperform after fees on average, some managers can add value in particular contexts. At the same time, passive strategies can be enhanced by incorporating factor-driven, evidence-based design elements.

2.2.2 Rise of Smart Beta ETFs

Smart beta strategies have gained increasing popularity among institutional investors aiming to fine-tune portfolio risk and performance while avoiding the high costs of traditional active management. While passive investing generally follows market-capitalization-weighted indices, smart beta deviates from this structure by using alternative weighting schemes based on fundamental or factor-based metrics. In this context, smart beta is often described as a "hybrid approach that blurs the line between active and passive investing" (Dziubinski, 2015). It preserves the transparent and rules-based nature of index investing, while at the same time actively shifting portfolios toward factors. Smart Beta ETFs typically track specialized indices designed to target factors such as value, low volatility, momentum, profitability, size, or combinations of these. These strategy indices are constructed via transparent rules. For example, selecting stocks based on dividend yields or volatility rankings, with periodic rebalancing, rather than discretionary stock picking. Because of their rules-based nature, Smart Beta ETFs are often categorized as passive investments. However, unlike a broad cap-weighted index, they incorporate active factor exposures by moving away from market capitalization weightings. A Smart Beta index predefines its selection and weighting rules and does not make explicit forecasts, yet it actively departs from the market portfolios exposures. Furthermore, the rebalancing period is also an active component. Smart Beta ETFs are not market-capitalization-weighted, as they do not automatically adjust to price changes in the way capitalization-weighted indices do. Instead, they must be periodically rebalanced to realign the portfolio with the chosen factor criteria and weights. This typically occurs on a set schedule (e.g. quarterly, semi-annually, or annually). Frequent rebalancing keeps the funds exposures updated, but it also introduces higher turnover and transaction costs than a purely passive buy-and-hold market index (Jacobs & Levy, 2015). These design parameters (factor selection, weighting, and rebalancing) collectively give Smart Beta ETFs their hybrid character.

In practice, many smart beta funds behave similarly to active funds that systematically shift toward factors. In order to understand these ETFs' performance, the factor exposure analysis is important to understand. For example, an index that screens and equally weights the top 100 value stocks will behave differently from one that assigns weights proportional to each stocks value score. As (Ung & Luk, 2016) observe, smart beta strategies seeking to capture the same factor can nonetheless end up with unequal factor and sector exposures due to such design variations. Most commonly, researchers use asset pricing models to attribute broader risk factors of a Smart Beta ETF's returns. For example, a low-volatility ETF might have a negative correlation to the market beta and size factors, as it often targets stable, large-cap stocks. Recent literature supports that thesis, but sometimes also shows unexpected exposures. (Glushkov, 2015), who covered 164 Smart Beta ETFs, could not find a significant outperformance of the risk-adjusted returns compared to the selected capitalization-weighted benchmarks. He found that only 60% of the sampled Smart Beta ETFs performed better than their benchmarks, earning an average of 1.16% more per year. The remaining 40% did worse, losing an average of 1.82% per year compared to their benchmarks. More concerning, the most popular Smart Beta ETF, which focuses on dividends, performed the worst, lagging behind by 3.90% annually. In other words, these ETFs excess returns could be explained by exposures to known factors like size, value or momentum, leaving no significant alpha beyond those factors. He also found that many funds had unintended exposures to other factors, which reduced the benefits of their main strategy. For example, a dividend ETF might accidentally favor small-cap or more highly indebted companies, weakening its intended advantage. The findings also showed that most of the performance came from constant exposure to certain factors, not from trying to time those factors through rebalancing. This supports the idea that Smart Beta ETFs mainly earn returns from their systematic factor approach, not from active stock picking.

But there is no such thing as consistency among these Smart Beta ETFs. (Brown et al., 2020) find that while these ETFs aim to target specific factors, actual exposures vary widely. On average, only about 56% of a Smart Beta ETFs risk was explained by its main factors, with some as low as 10%, indicating substantial unintended exposures.

Notably, some value ETFs even showed negative value loading. On average, there was a strong exposure to the size factor with a mean observed small-capitalization beta of 0.76. However, it can also be seen that there is a low exposure to the factors that are supposed to be the driving factors. Value and momentum labeled ETFs only showed an average beta of 0.25 and 0.09. Furthermore, there is a wide variation across funds, while some funds achieve high factor betas, others in the same labeled category barely differed from the market. Two ETFs in the same category may behave quite differently, depending on how their construction methodologies are designed.

In general, researchers use detailed factor regressions to assess how much of a Smart Beta ETFs return comes from exposure to systematic factors rather than from residual alpha. As pointed out later in this paper, most studies agree that these ETFs primarily generate returns through their exposures to targeted factors, with little consistent alpha remaining once those factors and any sector effects are considered.

2.2.3 Risk-Return Tradeoffs

A central promise of Smart Beta ETFs is an improved risk-return profile compared to traditional index funds and even to many actively managed funds. By selecting stocks with certain factors that have historically earned above-market returns or exhibited lower risk, smart beta strategies aim to deliver higher risk-adjusted returns than a standard market portfolio. The theoretical foundation comes from decades of asset pricing research, which have already been introduced earlier. Studies by (Fama & French, 1992, 1993) showed that size and value factors explain stock returns and carry long-term premiums, (Carhart, 1997) added momentum as a factor, and countless other studies have identified factors (quality, investment, profitability, etc.) that may yield excess returns or reduce downside risk. Smart Beta ETFs essentially package these factor-investing insights into investable index products. In principle, tilting toward proven factors should reward investors over the long run, either via outperformance by capturing additional return premiums or via risk mitigation. An example, therefore, is a low-volatility index, aiming for market-like returns with lower volatility. Notably, some smart beta strategies are return-oriented and seek higher returns than the index through factors like value or momentum, while others are risk-oriented and seek lower risk or volatility than the index. Empirical evidence on the risk-return tradeoff of Smart Beta ETFs has been growing, especially in recent years, and it presents a nuanced picture. Early research and backtests were often optimistic. The performance of Smart Beta ETFs has already been covered earlier in this paper. Some research highlights underperformance or limited advantage over traditional benchmarks (Glushkov, 2015; Rompotis, 2019), while others report stronger results for certain strategies or time periods (Arnott et al., 2005; Bowes & Ausloos, 2021; Mateus et al., 2020). Also, (Johnson, 2017a, 2017b) found that, based on a 10-year sample of U.S.-domiciled Smart Beta ETFs, there was no clear improvement in risk-adjusted performance compared to capitalization-weighted ETFs. Overall, the evidence reflects that outcomes vary depending on the strategy, factor exposure, and market conditions.

From a theoretical perspective, smart beta strategies aim to earn excess returns by taking on specific factor risks or focus on improving risk-adjusted returns by reducing market risk. However, deviating from capitalization-weighted benchmarks introduces tracking error and reduces diversification, meaning performance can vary significantly depending on whether the chosen factors are in or out of favor. Smart beta strategies can introduce diversification risks by deviating from cap-weighted benchmarks. (Jacobs & Levy, 2015) note that these strategies often become concentrated in certain sectors, such as financials in value indexes or utilities in dividend-weighted funds, leading to higher idiosyncratic or sector risk. In contrast, Multifactor Smart Beta ETFs aim to reduce such risks by blending factors like value, momentum, quality, and low volatility. Studies by (Chow et al., 2018) and (F. Li & Shim, 2019) show that this diversified approach can improve performance consistency and lower tracking error.

In conclusion, compared to traditional active management, smart beta strategies offer a potentially more favorable risk-return tradeoff. While active mutual funds often underperform after fees, Smart Beta ETFs provide low-cost, rules-based exposure to similar return drivers, such as value or momentum, often with better net results. For instance, a value ETF may charge only 0.2% in fees versus 1% for an active fund, offering more cost-effective access to the value premium. Industry surveys and research suggest smart beta is reshaping portfolio management by improving diversification, enhancing risk-adjusted returns, and offering downside protection through factor tilts like low volatility (Giampaoli, 2025). However, Smart Beta is not without trade-offs. Investors are exposed to factor-specific risks and performance volatility, especially in the short to medium term. The popularity of certain factors may also erode future returns (factor crowding), and real-world frictions like trading costs and tracking error can reduce effectiveness.

2.3 Smart Beta ETF Factors in Crises

2.3.1 Pre-Crisis Performance

The 2008 Global Financial Crisis was one of the harshest financial downfalls since the Great Depression. The crisis began with the collapse of the U.S. housing bubble and the failure of mortgage-backed securities, quickly spreading to global markets. As a result, the crisis caused widespread financial instability, mass bankruptcies, and a severe economic downturn. During the GFC, markets experienced dramatic losses, with the S&P

500 declining by approximately 50% from peak to bottom. The performance of smart beta factors during this period was mixed, reflecting their different sensitivities to market stress. In particular, the momentum factor demonstrated remarkable resilience in the crisis phase. A long-short momentum strategy, which involves buying past winners and selling past losers, generated a positive return of roughly 22% in 2008 (Smoler-Schatz, 2024). This aligns with the findings of (Daniel & Moskowitz, 2016), who documented the strong performance of momentum during crisis periods. However, momentum's strong performance did not last long. In early 2009, as the market began to recover, momentum strategies experienced a sharp fallback, with returns dropping by about 55%. This "momentum crash" occurred because previously underperforming stocks rebounded sharply, negatively impacting strategies that had shorted them. This highlights that factor performance can be highly dependent on market conditions and that momentum strategies are particularly sensitive to sudden shifts in market direction. In contrast, the value factor, which focuses on buying stocks that appear cheap based on measures such as P/B or P/E ratios, performed poorly during the GFC. Portfolios built around those stocks dropped sharply in 2008 and stayed weak in early 2009 (Ilmanen, 2023). Although (Fama & French, 1992) already argued that value stocks tend to do well in the long run, the GFC showed that they can struggle a lot during major financial crises.

2.3.2 COVID-19 Pandemic

The onset of the COVID-19 pandemic in February 2020 led to one of the fastest equity market declines in history. In roughly one month, global equities entered a bear market, with the MSCI AllCountry World Index falling over 21% in Q1 2020 and the S&P 500 dropping about 34% at its low on March 23 (Varsani et al., 2020). This sharp collapse offered a real-time test of defensive versus pro-cyclical factor performance. Empirical analyses show that factor indexes behaved largely as expected during the COVID crash: ETFs targeting defensive style factors drew smaller losses on average, while those tied to cyclically sensitive factors suffered deeper drawdowns (Invesco Quantitative Strategies, 2020). Low volatility and quality strategies, which tilt toward stocks with stable earnings, strong balance sheets, and lower market beta, mitigated the drawdown relative to the broad market. Momentum strategies also held up relatively well, partly due to their pre-crisis positioning in technology and other winners that proved resilient during the lockdowns. Similarly, the size factor underperformed significantly, consistent with past crises where smaller firms tend to be more vulnerable. In short, COVID-19s sudden shock rewarded the higher-quality, lower-risk segments of the market while punishing value and small-cap exposures.

Several studies provide further insight into how different factor strategies and investor behaviors evolved in this environment. When examining the behavior of equity factors during the crisis, (Hasaj & Scherer, 2021) found that momentum and quality factors were relatively more resilient in the initial sell-off. The momentum design helped it to adapt quickly to the changing market conditions, while quality strategies held up due to their focus on financially strong companies. However, low-volatility strategies struggled during the recovery phase, likely because of their defensive structure characteristics. Importantly, Hasaj and Scherer argue that sector exposures drove much of the return differences among factor ETFs. They highlight that index construction and timely rebalancing, especially for momentum strategies, played a critical role in effectively navigating the crisis. Turning to value investing, (D. Blitz & Hanauer, 2021) documents that value strategies underperformed early in the crisis, particularly those related to severely affected sectors. However, they observed a substantial recovery by early 2021, which they attribute mainly to valuation normalization rather than macroeconomic drivers. Adjustments for sector and risk exposure further improved the performance of these strategies. (D. Blitz et al., 2020) adds to this discussion by examining the role of short positions in factor investment. Although they do not directly assess Sharpe ratios during COVID-19, they argue that understanding risk-adjusted performance requires close attention to factor construction, particularly in volatile markets. Although factor construction shaped returns, investor flows played a crucial role in intensifying performance outcomes. (Pástor & Vorsatz, 2020) show that mutual fund investors responded strongly to short-term performance, reallocating capital away from underperforming funds toward better performing ones. This behavior contributed to the widening gap in fund outcomes during the crisis.

2.3.3 The Russia-Ukraine War

The year 2022 brought a very different kind of market stress. In contrast to the brief, V-shaped pandemic crash (see Figure A.1), 2022 saw a prolonged bear market driven by increased inflation, rising interest rates, and geopolitical conflict (Russias invasion of Ukraine). Although the conflict was geographically centered in eastern Europe, its financial repercussions were far-reaching. Numerous studies have shown that the war affected global stock, commodity, and currency markets, increasing volatility and altering market connectivity patterns. This environment of inflationary shock and monetary tightening had almost the opposite factor outcomes to 2020s deflationary panic. Notably, value stocks dramatically outperformed growth stocks in 2022, breaking a long stretch of values underperformance. Investors rotated out of high-valuation, growth-oriented names (which are sensitive to rising rates) and into cheaper segments like energy, utilities, and financials that benefited from inflation and higher yields. As a result, value-factor ETFs proved to be among the best performers in 2022, often delivering positive relative returns and in some cases even flat or modestly positive absolute returns (Abernathy, 2023). However, despite a growing body of research on general market reactions, a notable gap remains: there is still limited peer-reviewed academic work specifically examining how Smart Beta ETFs and factor investing strategies performed during this conflict, particularly in terms of factor loadings and risk-adjusted returns. Several empirical papers confirm that the war substantially altered financial market behavior. (Boungou & Yatié, 2022) observed sharp negative reactions in the stock market, especially in Europe, immediately after the invasion. (Kumari et al., 2023) found that although most EU markets experienced significant declines, a few showed resilience in the days that followed, suggesting heterogeneous effects likely related to geographic and economic factors. (Umar et al., 2022) showed that financial markets became more interconnected after the war began and that shocks spread more quickly between regions. (Zhang et al., 2025) added that the global commodity and stock markets developed stronger dependencies, highlighting the systemic nature of the financial impact of the conflict. Beyond traditional asset classes, studies have also explored specific themes and submarkets. (Obi et al., 2023) documented abnormal losses in the G7 equity markets and gains in commodity futures, highlighting how developed markets may be more sensitive to geopolitical disruptions than expected. Although these articles expand our understanding of market-wide impacts, they generally do not disaggregate outcomes by factor exposure or Smart Beta ETF structure. To my knowledge, no peer-reviewed study has thoroughly analyzed how Smart Beta ETFs adjusted their factor exposures or how factor loadings evolved during the war period. This is a significant oversight given the growing role of factor-based investing in both institutional and retail portfolios. Smart beta products, which tilt toward factors like value, momentum, quality, or low volatility, are often assumed to provide diversification and robustness across market cycles. However, their actual behavior during geopolitical stress remains underexamined.

2.4 Summary

The literature on asset pricing, factor investing, and Smart Beta ETFs reflects a broad empirical consensus but also reveals important gaps and areas of ambiguity. Smart Beta ETFs translate the commonly known factor insights of previous research on asset models into systematic, rules-based investment products that aim to combine the cost-efficiency of passive investing with the strategic advantages of active tilts. Research shows that most Smart Beta ETFs derive their performance primarily from static factor exposures rather than from alpha generation or timing, and that design choices, such as weighting methodology and rebalancing frequency, significantly influence outcomes. However, empirical studies also highlight inconsistencies in factor exposures across similarly labeled

ETFs, as well as unintended tilts that can dilute or contradict the intended strategy. During periods of market stress, factor performance has varied widely. Momentum and quality factors tended to hold up well during the COVID-19 crisis, while value and size underperformed. Conversely, value strategies performed strongly in the inflation-driven, rate-sensitive environment of 2022 following the RussiaUkraine conflict. Despite this, peer-reviewed research analyzing Smart Beta ETF behavior specifically during geopolitical crises remains limited. Existing studies focus predominantly on general market reactions without disaggregating outcomes by factor exposure or ETF structure. Overall, the literature supports the conceptual validity and practical relevance of smart beta strategies, particularly in delivering long-term, factor-driven returns at lower costs. Nonetheless, important research gaps remain. These include inconsistent factor targeting, the role of investor behavior, the performance implications of rebalancing and transaction costs, and the underexplored impact of geopolitical shocks on Smart Beta ETF performance. As we address these gaps, particularly regarding how factor exposures and performance behave during crisis periods such as the COVID-19 pandemic and the Russia-Ukraine war, we contribute to the existing literature by extending the current understanding of Smart Beta ETFs under stress conditions. These events serve as natural experiments for testing factor robustness, yet remain underexplored in the context of ETF structure, dynamic loadings, and design-specific outcomes.

3 Methodology

This thesis follows an empirical and quantitative research design. It is empirical because it uses real historical return data from over 200 Smart Beta ETFs, and quantitative because it applies regression analysis and factor models to measure risk exposures. The ETFs are grouped into four categories: momentum, low volatility, dividend, and multifactor. The analysis focuses on two major crisis periods - the COVID-19 pandemic and the Russia-Ukraine war - to study how these different strategies behaved during times of market stress. The research is both explanatory and comparative. It aims to explain how exposure to systematic risk factors influenced ETF returns during the crises and to compare the results across different regions (US and EU), ETF types, and model specifications. This approach helps to better understand how rule-based investment strategies react under pressure and which risk factors had the strongest impact. The following section outlines the research methods of this paper, covering the framework used for the analysis of factor exposure and performance of Smart Beta ETFs. Focusing on the two recent shocks, COVID-19 and the Russia-Ukraine war, this section explains the econometric models, performance metrics, and statistical robustness tests. By addressing that, the methodology section provides a solid foundation for the following evaluation of how Smart Beta ETFs behave under extreme market situations.

3.1 Data Sample

The data used in this analysis stems from two financial data providers: FactSet and VettaFi. FactSet is a popular and globally established financial data provider that offers market information and analytics. It was used to download historical daily prices for all ETFs in the sample, covering the period from January 2005 to December 2024. This results in a maximum of 5,032 observations per ETF. On the other hand, VettaFi, specialized in ETF data, delivers detailed and up-to-date information on ETF classifications, index methodologies, and selection criteria. Its focus on ETF analytics and full coverage of the ETF lifecycle makes it a reliable and authoritative source for research on fund characteristics and strategy definitions. As shown in Table 3.1, many of the ETFs in this analysis were already closed before 2024 or opened later than 2005, leading to a difference in average observations per asset in all categories. The study includes 212 Smart Beta ETFs, grouped within the factors low volatility, momentum, dividend, and multifactor. This data sample is a selection based on several criteria and filters. According to VettaFi, there are a total of approximately 9000 ETFs that fall into the category of "Smart Beta".

Table 3.1: Smart Beta ETF Clusters

Factor	ETFs	US	EU	∅ Obs.	COVID-19	Russia-Ukraine War
Momentum	23	19	4	3293	23	23
Dividend	80	39	41	2880	37	71
Low Volatility	33	17	16	1944	27	21
Multi-factor	66	29	37	2547	58	62
Total	202	104	98	-	145	178

Note: This table categorizes the 202 Smart Beta ETFs across four factor strategies (momentum, dividend, low volatility, multifactor) and by region (US and EU). It also reports the number of return observations and the count of ETFs active during two major crises: COVID-19 and the Russia-Ukraine War.

But, not all of them fit our criteria. For example, leveraged and inverse ETFs were excluded from the analysis, as they are designed for short-term trading rather than long-term investing. These products use daily rebalancing and techniques that cause compounding effects and path dependency, which makes them impractical for panel regression analysis. The dividend Smart Beta ETFs were chosen on the basis of their underlying selection criteria. Only Smart Beta ETFs with high dividend yields as screening criteria were included to ensure consistency within the category. This means that the ETFs focus on stocks that pay above-average dividends or have strong dividend growth rates. The same applies to momentum and low volatility ETFs. For the momentum category, only ETFs were included that track stocks from countries that have shown the best performance in the 6 and 12 months prior to the last rebalancing date. These ETFs usually rebalance periodically to react to price trends. Low volatility Smart Beta ETFs were selected based on their objective of minimizing return fluctuations. Therefore, ETFs with low historical volatility, mostly measured by standard deviation, were considered. Lastly, the multifactor ETFs in this study include ETFs that combine two or more factor strategies into one product. Unlike the other ETF categories, these funds were not chosen on the basis of specific selection rules. Instead, they follow different strategies depending on how each provider builds their index. This group is used as a 'control' group to compare with single-factor Smart Beta ETFs. Including multifactor ETFs helps to show whether there are clear differences between ETFs that focus on one factor and those that blend several.

The geographical classification of our Smart Beta ETFs is separated into Europe and North America. Although Mexico is not part of the selected countries, the ETFs for North America may contain assets from Canada. For simplicity, we use the terminology "US" to refer to North American ETFs. In order to investigate the Smart Beta ETF returns, the factors for the different models are provided by the Fama-French Data Library (French, 2025). All returns for the factors MRP, SMB, HML, RMW, and CMA are not

Table 3.2: Smart Beta ETF Selection Criteria

Category	Selection Criteria
Dividend	ETFs that use high dividend yield as a primary screening criterion. Focus is on stocks with above-average dividend payouts or strong dividend growth rates.
Momentum	ETFs that select stocks based on recent price performance, typically over 6- and 12-month periods prior to the most recent rebalancing.
Low Volatility	ETFs that aim to reduce return fluctuations by investing in stocks with low historical volatility, generally measured by standard deviation.
Multifactor	ETFs that combine two or more factor strategies (e.g., value, momentum, quality, volatility). No uniform selection criteria; strategies vary by provider. Used as a control group in this study.

Note: This table summarizes the selection criteria applied to classify Smart Beta ETFs into factor categories for the purposes of this study.

continuously compounded, and hence display arithmetic (simple) returns. The MRP is the return of a region's value-weight market portfolio minus the US one-month T-bill rate (risk-free rate). To account for regional differences, the same Fama-French factor returns were also obtained for the European market. These EU-specific factors ensure that the regression analysis reflects the appropriate regional risk premia for ETFs focused on European equities. To analyze the effects of major external shocks, two event periods were defined. The COVID-19 period spans from February 1, 2020, to December 31, 2020, capturing both the initial market collapse and the partial recovery that followed. The Russia-Ukraine war period covers February 24, 2022, to December 31, 2022, starting with the invasion date and reflecting the financial impact of the conflict throughout the year. These time frames allow for a focused analysis of how ETF performance and factor sensitivities respond to significant geopolitical and economic disruptions. To provide a consistent and objective performance assessment, each strategy is evaluated using a portfolio composed of all relevant ETFs in the category, rather than analyzing individual ETFs. This approach tackles the challenges posed by the different inception dates of ETFs, the varying size of the assets, and the disproportionate influence of single ETFs. For comparison purposes, multiple benchmarks are used.

Table 3.3: Overview of Factor Portfolios and their respective benchmark

Ticker	**Benchmark ETF**
Momentum US	iShares MSCI USA Momentum Factor ETF
Dividend US	iShares Select Dividend ETF
Low Volatility US	Invesco S&P 500 Low Volatility ETF
Multifactor US	SPDR S&P 500 ETF
Momentum EU	SPDR S&P 1500 Momentum Tilt ETF(*)
Dividend EU	SPDR S&P Euro Dividend Aristocrats UCITS ETF
Low Volatility EU	SPDR EURO STOXX Low Volatility UCITS ETF
Multifactor EU	iShares STOXX Europe 600 UCITS ETF

Note: This table lists the factor portfolios used in the study along with their respective benchmark. (*) marks the momentum benchmark ETF for Europe, although it covers US territory. This is due to the absence of a suitable broad momentum ETF in Europe.

As shown in Table 3.3, a factor-specific index ETF is selected to serve as the primary benchmark to calculate the benchmark ratio, reflecting the targeted investment strategy. In addition, a broad-market ETF is included for each geographic region to provide a general market comparison. For multifactor strategies, only broad market benchmarks are used, as no single index can adequately represent the diverse exposures involved. Furthermore, due to the absence of a suitable broad momentum ETF in Europe, a broad American version has to be utilized in this analysis. This method ensures a more accurate and independent evaluation, avoiding potential biases from fund-provider-selected benchmarks. A detailed list of each Smart Beta ETF and Benchmark ETF used in this study can be found in Table A.2. Lastly, all initial data cleaning and pre-processing was performed using Microsoft Excel. This included merging datasets, formatting columns, and organizing date variables for consistency and clarity. The subsequent empirical analysis was performed in Stata 18 MP (Parallel Edition). Stata was used to generate descriptive statistics and perform panel regressions, as well as provide performance measurements, graphics, and summaries.

3.2 Data Variables

The dependent variable is the respective ETF excess return, defined as the ETF's daily return minus the risk-free rate. Formally, for ETF i at time t, the excess return is:

$$R_{i,t}^{\text{excess}} = R_{i,t}^{\text{ETF}} - R_{f,t}$$

where $R_{i,t}^{\text{ETF}}$ is the return of ETF i at time t, and $R_{f,t}$ is the corresponding risk-free rate. The risk-free rate is, as described above, the risk-free asset in the market (here US one-month T-bill rate). Using excess returns as the dependent variable ensures that performance is measured relative to a risk-free baseline, consistent with asset pricing theory. The independent variables in this analysis are standard risk factors derived from established asset pricing models, specifically the Fama-French three- and five-factor models, the Carhart four-factor model, and an extended six-factor specification. These factors were obtained from the Kenneth R. French Data Library, a widely recognized and commonly used source in academic finance. A detailed description of the calculation for all factors, consistent with the methodology used by Fama and French, is provided by (French, 2025).

Market Risk Premium (MRP): MRP represents the excess return of a market portfolio over the risk-free rate. It is the classic CAPM factor that represents the risk of the broad market. It is calculated as the region's value-weighted market portfolio minus $R_{f,t}$. A positive loading on MRP indicates that the asset moves with the market.

SMB (Small Minus Big): In this case, SMB is the average return on the nine small stock portfolios minus the average return on the nine large stock portfolios. The size factor reflects the historical tendency of smaller firms to generate higher returns than larger firms. A positive SMB loading indicates that the ETF has greater exposure to small-cap stocks.

HML (High Minus Low): The value factor is defined as the difference in return between stocks with high book-to-market ratios (value stocks) and those with low book-to-market ratios (growth stocks). It captures the value premium, where a positive loading indicates that an ETF is more exposed to value-oriented stocks.

RMW (Robust Minus Weak): The profitability factor, introduced in the five-factor model of (Fama & French, 2015), captures the return differential between firms with robust (high) operating profitability and those with weak (low) profitability. A positive RMW loading suggests that the ETF has greater exposure to companies with strong earnings performance.

CMA (Conservative Minus Aggressive): The investment factor, also introduced in the five-factor model, measures the return spread between firms that follow conservative investment strategies (low asset growth) and those that invest more aggressively (high asset growth). A positive CMA loading indicates that the ETF is more exposed to firms with restrained investment behavior, reflecting a preference for companies that tend to outperform by maintaining lower levels of capital expansion.

WML (Winners Minus Losers): The momentum factor, first captured by (Carhart, 1997) as an extension of the Fama-French framework, captures the return differential between stocks that have performed well and those that have performed poorly over the previous 12 months. It is typically constructed as a longshort portfolio, going long on recent winners and short on recent losers. This factor reflects the momentum effect, where past performance tends to persist in the short term. ETFs designed to follow a momentum strategy are therefore expected to exhibit a strongly positive loading on the WML factor.

These six factors represent widely recognized risk premia in the asset pricing literature. The foundational Fama and French three-factor model incorporates the market risk premium (MRP), size (SMB), and value (HML). (Carhart, 1997) later extended this framework by adding a momentum factor (WML), creating the four-factor model. The five-factor model introduced by (Fama & French, 2015) added two additional dimensions: profitability (RMW) and investment (CMA). The extended six-factor model applied in this study combines all of these components. Including all six factors enables the analysis to account for key systematic risk sources and style exposures that are likely to influence the return behavior of Smart Beta ETFs.

3.3 Factor Models

To examine the factor exposures of different Smart Beta ETFs, this study investigates the key variables of the most widely used asset pricing models. Using panel regression techniques, we evaluated the cross-sectional factor loadings that best explain the return variation between ETFs.

The Fama-French three-factor model, first introduced in 1993, has become a foundational tool in empirical asset pricing. Building on the theoretical framework of the Capital Asset Pricing Model (CAPM), it aims to address systematic anomalies that CAPM fails to explain. Although CAPM describes expected returns as a function of market risk alone, empirical evidence, outlined in the theory section, has shown that certain categories of stocks tend to earn higher returns than predicted by this model. (Fama & French, 1993) identified two such patterns: small firm stocks and those with high book-to-market ratios systematically outperform expectations based on CAPMs single risk factor. To account for these effects, they introduced two additional factors into the pricing model: the size factor (SMB) and the value factor (HML). These augment the traditional market risk premium (MRP) and together aim to capture variations in expected returns across different stock characteristics. Using the Fama-French three-factor model, the following equation applies to our analysis:

$$R_{i,t}^{\text{excess}} = \alpha_i + \beta_M MRP_t + \beta_S SMB_t + \beta_H HML_t + \varepsilon_{i,t},$$

where α_i represents the intercept term (also known as alpha), β_M, β_S, and β_H are the factor loadings on the market risk premium (MRP), size (SMB) and value (HML), and $\varepsilon_{i,t}$

denotes the error term. While the Fama-French three-factor model incorporates market, size, and value factors to explain stock returns, it does not account for the well-documented momentum anomaly. To address this, (Carhart, 1997) extended the model by including a fourth factor (WML), which captures the tendency of stocks that performed well in the recent past to continue performing well in the short term. This adjustment resulted in the Carhart four-factor model, which has since become a widely used extension in empirical asset pricing. In this study, the Carhart four-factor model is based on the following equation:

$$R_{i,t}^{\text{excess}} = \alpha_i + \beta_M MRP_t + \beta_S SMB_t + \beta_H HML_t + \beta_W WML_t + \varepsilon_{i,t},$$

where α_i is the intercept (alpha), and β_M, β_S, β_H, and β_W are the factor loadings on the market risk premium (MRP), size (SMB), value (HML) and momentum (WML) factors. $\varepsilon_{i,t}$ is the error term. Although the Fama-French three-factor model has been widely used, later research showed that it did not fully capture all the key influences on stock returns. Studies by (Novy-Marx, 2013) and (Aharoni et al., 2013) found that companies with higher profitability and more cautious investment behavior tended to earn higher returns. To address this, (Fama & French, 2015) expanded their model to include two more factors: one for profitability (RMW) and one for investment (CMA). These additions helped the model explain the returns more accurately by considering that profitable and conservatively managed companies often perform better. The following equation was used in this paper:

$$R_{i,t}^{\text{excess}} = \alpha_i + \beta_M MRP_t + \beta_S SMB_t + \beta_H HML_t + \beta_R RMW_t + \beta_C CMA_t + \varepsilon_{i,t},$$

where α_i is the intercept, and β_M, β_S, β_H, β_R, and β_C represent the sensitivities to the market risk premium (MRP), size (SMB), value (HML), profitability (RMW), and investment (CMA) factors. $\varepsilon_{i,t}$ is the error term. To better capture all important drivers of returns, the extended six-factor model brings together the Fama-French five-factor model and the momentum factor introduced by Carhart. This expanded version includes six factors: market, size, value, profitability, investment, and momentum. By combining these elements, the model gives a more complete picture of the main risks and influences that shape the performance of Smart Beta ETFs.

$$R_{i,t}^{\text{excess}} = \alpha_i + \beta_M MRP_t + \beta_S SMB_t + \beta_H HML_t + \beta_R RMW_t + \beta_C CMA_t + \beta_W WML_t + \varepsilon_{i,t},$$

where α_i is the intercept, and β_M, β_S, β_H, β_R, β_C, and β_W are the loadings on the market (MRP), size (SMB), value (HML), profitability (RMW), investment (CMA), and momentum (WML) factors respectively. $\varepsilon_{i,t}$ is the regression residual.

3.4 Panel Regression

To investigate the relationship between factor exposures and Smart Beta ETF returns across time and categories, this study uses a panel data regression framework. Panel regressions in general are particularly well suited for financial datasets that combine cross-sectional and time series dimensions, as is the case with Smart Beta ETFs observed daily over multiple years. Panel data models offer several key advantages. First, they allow for controlling unobservable heterogeneity by incorporating entity-specific effects, such as ETF characteristics that remain constant over time but could influence returns (Baltagi, 2021; Hsiao, 2003). This is particularly relevant in ETF analysis, where structural features such as rebalancing frequency or issuer practices may not vary across months but still affect performance. Second, panel models improve estimation efficiency by exploiting variation across both ETFs and time, thereby increasing the degrees of freedom and reducing the risk of omitted variable bias. To estimate the relationship between ETF excess returns and systematic risk factors under stress periods, we employ both fixed effects (FE) and random effects (RE) panel regressions. To examine how factor exposures behave under stress, we implement both fixed effects (FE) and random effects (RE) models. While the FE model controls for ETF-specific traits, the RE model accommodates time-invariant variables, making it suitable for broader generalizations. A central feature of our model specification is the inclusion of interaction terms between asset pricing factors and crisis dummy variables (e.g., COVID-19 or the Russia-Ukraine war). These interaction terms are crucial for detecting changes in factor sensitivity during crisis periods. In essence, the interaction terms capture whether and how the relationship between factor exposures (e.g., value, momentum, quality) and ETF returns shifts under stress. A significant interaction coefficient indicates that the factors influence on returns is different during crisis periods compared to normal times. This provides insights into the time-varying nature of factor performance and the resilience or vulnerability of Smart Beta strategies under market shocks. Let i denote an ETF and t denote time (e.g., months or days). Let D_t be a binary crisis dummy variable (*c19* for COVID-19 or *war* for the Russia-Ukraine War). Our core specification includes interactions between the crisis dummy and asset pricing factors.

Fixed Effects (FE) Model:

$$\text{Excess}_{i,t} = \alpha + \sum_{k=1}^{K} \beta_k (X_{k,i,t} \times D_t) + \mu_i + \epsilon_{i,t}, \tag{3.1}$$

where:

- $X_{k,i,t}$: factor exposures (e.g., MRP, SMB, HML, WML, RMW, CMA)
- D_t: crisis dummy variable (e.g., *c19*, *war*)
- μ_i: unobserved, ETF-specific fixed effect
- $\epsilon_{i,t}$: idiosyncratic error term

This model uses the within transformation to eliminate μ_i, thus controlling for all time-invariant characteristics specific to the ETF.

Random Effects (RE) Model:

$$\text{Excess}_{i,t} = \alpha + \sum_{k=1}^{K} \beta_k (X_{k,i,t} \times D_t) + u_i + \epsilon_{it}, \tag{3.2}$$

where:

- $X_{k,i,t}$: factor exposures (e.g., MRP, SMB, HML, WML, RMW, CMA)
- D_t: crisis dummy variable (e.g., *c19*, *war*)
- $u_i \sim \mathcal{N}(0, \sigma_u^2)$: ETF-specific random effect, assumed uncorrelated with $X_{k,i,t}$
- $\epsilon_{i,t}$: idiosyncratic error term

This model retains u_i and estimates its variance component, assuming that ETF-specific effects are uncorrelated with regressors. Based on the results of the Hausman test, we determine whether the fixed effects or random effects specification is more appropriate for each case. The preferred model is then used to estimate the factor loadings, which capture how ETF exposures to systematic risk factors vary during crisis periods. These estimated loadings form the basis of our subsequent analysis, allowing us to assess whether and how ETF return sensitivities to risk factors differ across investment styles, regions, and stress regimes.

3.5 Estimation Diagnostics and Model Validation

To ensure the validity and robustness of the panel regression results, several diagnostic tests were applied to assess the underlying econometric assumptions and to validate the estimation strategy. These diagnostics address key issues such as autocorrelation, multicollinearity, and overall accuracy of the model.

3.5.1 Hausman Test

In panel data analysis, the decision whether to use Fixed Effects (FE) or Random Effects (RE) is a critical step to receive reliable regression estimates. The key distinction lies in how the two models treat unobserved individual effects, denoted as α_i. The FE model assumes that these effects may be correlated with the explanatory variables, while the RE model assumes that they are uncorrelated. Given the structure of this study, which examines how Smart Beta ETFs respond to various risk factors, it is reasonable to assume that some ETF-specific traits, such as investment strategy, could be associated with their exposure to these factors. This potential correlation supports the use of the FE model. To formally test whether the assumptions behind the RE model are valid, the Hausman specification test is applied. This test compares the FE and RE estimators to evaluate whether the RE model produces consistent results.

$$H_0 : \text{Cov}(\alpha_i, X_{it}) = 0$$

$$H_1 : \text{Cov}(\alpha_i, X_{it}) \neq 0$$

The null hypothesis of the test states that the unobserved effects are uncorrelated with the regressors. If the test returns a ρ-value below 0.05, the null is rejected, and the FE model is chosen because it remains consistent when endogeneity is present.

3.5.2 Wooldridge Test

To check for autocorrelation in the panel regression model, the Wooldridge test for serial correlation in the panel data was applied. This test is commonly used with fixed effects (FE) models and detects whether the error terms for each cross-sectional ETF are correlated over time. The null hypothesis assumes that there is no first-order autocorrelation, which means that the error terms are not correlated across time within each unit, while the alternative suggests that such autocorrelation does exist (Wooldridge, 2010).

$$H_0 : \rho = 0 \quad \text{(no first-order autocorrelation)}$$

$$H_1 : \rho \neq 0 \quad \text{(first-order autocorrelation present)}$$

A significant test result ($\rho < 0.05$) leads to rejection of the null hypothesis, meaning that serial correlation is likely present. This can affect the accuracy of standard errors and make statistical results less reliable. We will discuss the specific results of the Wooldridge test later in the analysis. However, if first-order autocorrelation is detected, one appropriate way to address this issue is to use clustered standard errors. Applying the vce(cluster AssetID) option adjusts the standard errors to account for both autocorrelation and heteroskedasticity within each panel unit. Although the Wooldridge test is designed primarily for fixed-effects models, the logic of correcting for serial correlation applies more broadly. In the case of random-effects models, alternative tests may be required, but clustering still serves as a useful correction to ensure valid statistical inference.

3.5.3 Variance Inflation Factor (VIF)

An important step in checking the quality of a regression model is testing for multicollinearity. Multicollinearity happens when two or more explanatory variables are highly correlated with each other, making it difficult to estimate the individual effect of each variable. One of the most commonly used tools to detect multicollinearity is the Variance Inflation Factor (VIF). Introduced by (Farrar & Glauber, 1967), the VIF measures how much the variance of a coefficient increases due to collinearity with other variables. It is calculated by regressing each independent variable on all the others and then using the resulting R^2 value to calculate the VIF:

$$VIF_j = \frac{1}{1 - R_j^2}$$

The higher the VIF, the stronger the multicollinearity. Although the VIF does not rely on a formal hypothesis test, it provides useful thresholds for interpretation. A VIF greater than 10 is generally seen as a serious problem, while values between 5 and 10 may still raise concern. In some cases, especially with smaller samples or highly sensitive models, even VIF values above 2.5 or 3 can be observed. These thresholds are not strict rules, but they help guide decisions about model quality. Using VIF in this way helps ensure that each variable in the regression provides unique and reliable information. Keeping the VIF values low improves the precision of the model and increases confidence in the interpretation of the results.

3.5.4 Root Mean Squared Error (Root MSE)

To evaluate the overall accuracy of the panel regression models, the Root Mean Squared Error (Root MSE) was calculated. This metric captures the standard deviation of the residuals and provides a direct measure of the average prediction error between the actual and fitted values. In the context of this analysis, the Root MSE represents the average difference between the actual excess returns of the ETFs and the returns predicted by the model. A lower Root MSE indicates a better model fit, meaning that the predicted returns are closer to the observed ones. The MSE of the root is defined as:

$$\text{Root MSE} = \sqrt{\frac{1}{nT}\sum_{i=1}^{n}\sum_{t=1}^{T}\left(R_{i,t}^{\text{excess}} - \hat{R}_{i,t}^{\text{excess}}\right)^2},$$

where $R_{i,t}^{\text{excess}}$ is the actual excess return of ETF i at time t, $\hat{R}_{i,t}^{\text{excess}}$ is the predicted excess return from the model, n represents the number of ETFs, and T denotes the number of time periods in the panel. Unlike relative fit measures such as R^2, Root MSE provides an absolute indication of model performance.

3.6 Performance Measurements

To evaluate the risk-adjusted performance of the investment strategy, this study applies three widely recognized metrics: the Sharpe Ratio, the Sortino Ratio, and the Information Ratio. These measures provide insight into the relationship between returns and associated risk, allowing a comprehensive comparison of portfolio performance. Unlike the panel regressions conducted for the factor exposure analysis, which were based on simple returns, this performance analysis uses log returns. Log returns are preferred here as they offer better properties for evaluating cumulative performance, particularly due to their time-additive nature and consistency with compounding.

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right),$$

where:

- r_t is the log return at time t,
- P_t is the price at time t,
- P_{t-1} is the price at time $t-1$,
- ln denotes the natural logarithm.

3.6.1 Sharpe Ratio

The Sharpe ratio, developed by (Sharpe, 1966, 1994), measures the excess return of a portfolio over the risk-free rate, adjusted for total risk. It is defined as:

$$\text{Sharpe Ratio} = \frac{R_p - R_f}{\sigma_p},$$

where R_p is the mean return of the portfolio, R_f is the risk-free rate, and σ_p is the standard deviation of the portfolio returns. A higher Sharpe ratio indicates that the portfolio delivers more excess return per unit of total risk. Although widely adopted, the Sharpe ratio treats upside and downside volatility equally, which may not align with investor preferences. We also compute a rolling Sharpe ratio using a fixed 63-day moving window to capture how the portfolios risk-adjusted performance evolves over time. This approach involves applying the standard Sharpe ratio formula to each overlapping sub-period, enabling a dynamic view of return-to-risk efficiency. Rolling performance metrics are particularly valuable for identifying shifts associated with regime changes and periods of heightened volatility.

3.6.2 Sortino Ratio

The Sortino Ratio (Sortino & van der Meer, 1991) improves on the Sharpe Ratio by isolating the downside risk. It is calculated as:

$$\text{Sortino Ratio} = \frac{R_p - R_f}{\sigma_d},$$

where σ_d is the standard deviation of negative returns (returns falling below the minimum acceptable return, typically the risk-free rate). The rolling Sortino ratio is computed similarly in a fixed window to capture how downside risk-adjusted performance evolves. This is particularly relevant in volatile or bear market environments, where downside risk dominates investor concern.

3.6.3 Information Ratio

The Information Ratio (Goodwin, 1998) evaluates the excess return of a portfolio relative to the benchmarks determined in Table 3.3, scaled by tracking error.

$$\text{Information Ratio} = \frac{R_p - R_b}{\sigma_{(p-b)}},$$

Where:

- R_b is the return of the benchmark,
- $\sigma_{(p-b)}$ is the standard deviation of the difference between the portfolio and benchmark returns.

Also here, the rolling information ratio is computed by applying this formula to moving windows.

4 Empirical Analysis

4.1 Descriptive Statistics

Table 4.1 presents the descriptive statistics for the excess returns of the Smart Beta ETFs in our four categories: momentum, dividend, volatility, and multifactor across the US and EU. Statistics are reported for the full sample period and include the mean, standard deviation, minimum, and maximum of daily excess returns. We use in this text, for simplification, the percentage notation for the descriptive statistics.

Table 4.1: Descriptive Statistics for ETF Excess Returns by Category and Region

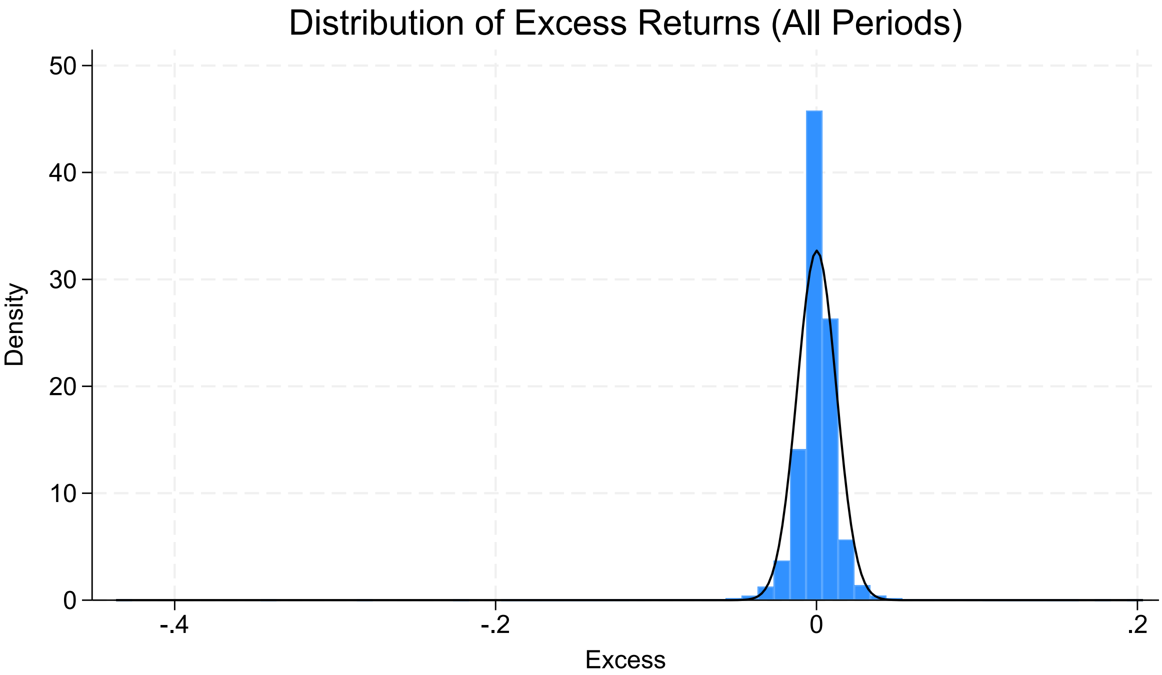
Category	Region	Mean	SD	Min	Max
Momentum	US	0.0001611	0.0151677	-0.3369351	0.1498011
	EU	0.0001473	0.0104991	-0.1381139	0.0815754
Dividend	US	0.0002107	0.0125332	-0.1859751	0.1772891
	EU	0.0000591	0.0117633	-0.1950000	0.1488675
Volatility	US	0.0002610	0.0105099	-0.1732251	0.1365604
	EU	0.0001413	0.0094749	-0.4365145	0.0924234
Multifactor	US	0.0002542	0.0120623	-0.2220340	0.1814048
	EU	0.0001896	0.0112908	-0.1846344	0.1984563

Note: This table presents the mean, standard deviation (SD), minimum, and maximum daily excess returns for Smart Beta ETFs, categorized by strategy (Momentum, Dividend, Volatility, and Multifactor) and region (US and EU). Excess returns are computed relative to the risk-free rate.

Among the categories, the Volatility and Multifactor ETFs in the US market show the highest average excess returns, at 0.0261% and 0.0254% per day. Conversely, the Dividend ETFs in the EU show the lowest mean return (0.0059%), suggesting limited reward over the risk-free rate for that segment during the sample period. The Momentum ETFs demonstrate relatively consistent mean returns across regions, indicating a degree of stability in their performance. Standard deviations indicate that US-based ETFs generally exhibit greater return volatility than their EU counterparts, consistent across all four ETF types. For example, the Momentum ETFs in the US have a standard deviation of 1.52%, compared to 1.05% in the EU. Interestingly, the Volatility ETFs, despite their objective of minimizing variance, show the lowest standard deviation in the EU (0.95%), although their minimum return (-43.65%) suggests exposure to extreme downside risk in rare events, potentially due to crisis-driven market distortions. The minimum and maximum values show how much returns can vary. The Momentum ETFs (US) and Volatility ETFs (EU) had the biggest losses, falling by -33.69% and -43.65% on their worst days.

This shows that they can drop a lot under tough market conditions. In contrast, the EU Multifactor ETFs and US Dividend ETFs had some of the biggest gains, showing that they can also perform very well at times. The Multifactor ETFs appear to offer a relatively favorable risk-return profile, particularly in the EU market, where they combine a solid average return with moderate volatility and a relatively contained maximum drawdown.

Fig. 4.1: Distribution of Excess Returns



Note: This histogram displays the distribution of daily excess returns for Smart Beta ETFs over the full sample period. It shows the overall shape of return behavior, including central tendency and tail risk.

The distribution of excess returns in Figure 4.1 exhibits a centered picture with the majority of values between -0.02 and 0.02, showing the majority of the observations clustered around the mean. Nevertheless, there are thin tails, especially to the left, indicating that there are extreme negative returns. During the COVID-19 crisis, the return distribution shifts significantly to the left, with a heavier lower tail and wider spread, indicating increased volatility and heightened downside risk (Figure A.2). This reflects market stress and amplified sensitivity of smart beta strategies to systemic shocks. In comparison, the Russia-Ukraine war period also shows greater tail risk relative to non-crisis periods, but the distortion is less pronounced than during COVID (Figure A.3). These shifts underscore the importance of accounting for regime-dependent risk dynamics when evaluating factor exposures and Smart Beta ETF performance.

In addition to ETF returns, the analysis also considers the behavior of the six key factor variables used in this study: MRP, SMB, HML, WML, RMW, and CMA. Table 4.2 summarizes their statistical properties during the sample period.

Table 4.2: Descriptive Statistics for Factor Variables

	MRP	SMB	HML	WML	RMW	CMA
Mean	0.0003442	-0.0000739	-0.0000733	0.0002202	0.0001306	0.0000021
SD	0.0116233	0.0052299	0.0072056	0.0088129	0.0036603	0.0043816
Min	-0.1200	-0.0530	-0.0448	-0.1207	-0.0242	-0.0282
Max	0.1072	0.0515	0.0663	0.0564	0.0418	0.0231

Note: This table reports summary statistics for the factors used in the six-factor model: MRP (market risk premium), SMB (size), HML (value), WML (momentum), RMW (profitability), and CMA (investment). Statistics include the mean, standard deviation (SD), minimum, and maximum of daily factor

In terms of factor variables, the market risk premium and the WML momentum factor stand out with the highest average daily returns, at 0.0344% and 0.0220%. In contrast, SMB and HML have slightly negative means of -0.0074% and -0.0073%, indicating weak performance by small-cap and value stocks over the sample period. The RMW factor posts a modest average return of 0.0131%, while CMA, with a near-zero return of 0.0002%, contributes the least. Volatility levels differ considerably across the factors. MRP has the highest standard deviation at 1.16%, followed by WML (0.88%) and HML (0.72%), confirming that these factors fluctuate the most. SMB follows with a moderate 0.52% standard deviation. On the other hand, RMW and CMA are relatively stable, with standard deviations of just 0.37% and 0.44%, respectively. When examining extreme values, MRP and WML show the most severe one-day losses, dropping as much as -12.00% and -12.07%. On the positive side, MRP also records the highest gain, peaking at 10.72%, while HML reaches 6.63%. These selected figures highlight both the return potential and the tail risks embedded in the factor exposures. MRP and WML, in particular, emerge as key drivers of variation, both in normal conditions and during times of market stress. This reinforces their expected relevance in the upcoming factor loading analysis.

4.2 Diagnostic Tests

This section presents the diagnostic tests and criteria used to guide the selection of models for the panel regression analysis.

Although initial model diagnostics, as seen in Table A.3, suggest a preference for random effects (RE) in most ETF categories and factor combinations, several compelling reasons support the use of fixed effects (FE) in this analysis. The Hausman test, while widely used, can yield unreliable guidance in small samples or when model assumptions are only weakly satisfied. (Clark & Linzer, 2015) argue that FE models are more robust in the presence of potential correlation between regressors and unit-specific effects, a common scenario in empirical finance. FE models effectively control for unobserved heterogeneity that is constant over time but varies across entities, such as investment strategy, target market, or management approach, which are not always captured in the data. Neglecting these unobserved traits can lead to biased estimates. Even when the Hausman test favors RE, researchers caution against relying solely on it. Already (Ahn & Low, 1996) highlight its limitations in detecting misspecification, especially with weak instruments or few observations. (Frondel & Vance, 2010) propose a variant of the Hausman test that examines the equality of between-groups and fixed-effects coefficients, offering a more nuanced assessment. In applied finance research, choosing FE is often more reliable, particularly when aiming to avoid bias from unmeasured ETF-specific characteristics. FE models also facilitate stronger causal interpretations by removing noise from time-invariant variables, which is especially beneficial when analyzing ETF responses to changing market conditions, such as during financial crises. While RE models can be more efficient under certain assumptions, FE models offer a safer alternative when those assumptions are in doubt. In the context of this thesis, FE models are more appropriate, as they provide more reliable results when examining how time-varying factors affect ETF returns during periods of market stress. Although the Hausman test suggests a preference for the random effects model in our case, we adopt the fixed effects specification based on stronger theoretical justification and concerns over unobserved heterogeneity. To account for potential heteroskedasticity and serial correlation in the panel data structure, all regressions were estimated using clustered standard errors at the AssetID level. This method ensures that inference remains valid in the presence of both within-asset autocorrelation and cross-sectional heteroskedasticity.

The Wooldridge test for autocorrelation, presented in Table A.4 and Table A.5, indicates that 64 out of 96 specifications show signs of serial correlation. However, many of these results are only marginally significant. The use of cluster-robust variance estimation effectively addresses both autocorrelation and heteroskedasticity, providing consistent coefficient estimates and reliable standard errors even when standard assumptions are violated.

Multicollinearity was assessed using the Variance Inflation Factor (VIF), as reported in Table A.4 and Table A.5. The mean VIF values across all model specifications remain well below conventional thresholds, with most falling under 2.5 and many closer to 2.0 or below. At the individual factor level, the VIFs are even lower, indicating a very low degree

Table 4.3: Correlation Matrix of Factor Returns

	MRP	SMB	HML	RMW	CMA	WML
MRP	1.0000					
SMB	-0.0404	1.0000				
HML	0.0029	0.1332	1.0000			
RMW	-0.1275	-0.2471	-0.2388	1.0000		
CMA	-0.2575	0.0176	0.7205	-0.0523	1.0000	
WML	-0.1911	-0.1282	-0.3322	0.1317	-0.0812	1.0000

Note: The table presents the pairwise correlations between the six factors: MRP (Market Risk Premium), SMB (Small Minus Big) representing the size factor, HML (High Minus Low) for value, WML for momentum, CMA (Conservative Minus Aggressive) for investment and RMW (Robust Minus Weak) for profitability.

of multicollinearity. These results confirm that multicollinearity does not pose a concern in the interpretation of model estimates. While the correlation matrix in Figure 4.3 shows generally low correlations across the six-factor model, the relatively high correlation between HML and CMA suggests some overlap. This presents a minor limitation, though the VIF results indicate that it does not materially distort the regression analysis. All key econometric assumptions have been addressed through appropriate diagnostic testing and estimation techniques. Heteroskedasticity, autocorrelation, and multicollinearity were tested and accounted for using cluster-robust standard errors and variance inflation factor analysis. Based on this foundation, model selection is guided by empirical performance measures. Root Mean Squared Error and adjusted R-squared are used to evaluate and compare models in terms of both predictive accuracy and explanatory power. To validate the specification of the model and ensure the appropriate explanatory power across markets, adjusted R-squared values were evaluated for all factor models during our two major crisis periods: the COVID-19 pandemic and the Russia-Ukraine war. As shown in Table 4.4, which reports the results from the COVID-19 period, the Carhart four-factor model consistently outperformed the Fama-French three-factor model and closely approached the explanatory strength of more complex specifications. The extended six-factor model delivered the highest adjusted R-squared values across several categories, particularly for momentum- and dividend-focused ETFs in both the US and EU markets. Similarly, Table 4.5 presents results for the war period, where both the Carhart and the six-factor models again showed superior and stable performance across all factor strategies and regions. Although the incremental gains of the six-factor model over the four-factor model were moderate, they were consistent and most pronounced in the EU sample, suggesting added value in capturing region-specific dynamics. The choice to use the Carhart and extended six-factor models is also supported by the way the adjusted R-squared works. Unlike the regular R-squared, the adjusted R-squared takes into ac-

Table 4.4: Adjusted R-Squared during COVID-19

Model	Momentum		Dividend		Volatility		Multifactor	
	US	EU	US	EU	US	EU	US	EU
3-Factor	0.7579	0.8515	0.8927	0.6693	0.8617	0.6896	0.8330	0.6400
4-Factor	0.7663	0.8659	0.8944	0.6693	0.8632	0.6952	0.8332	0.6417
5-Factor	0.7605	0.8541	0.8949	0.6706	0.8619	0.6910	0.8339	0.6400
6-Factor	0.7671	0.8698	0.8969	0.6707	0.8633	0.6975	0.8341	0.6416

Note: This table reports adjusted R-squared values for Smart Beta ETFs across various factor models during the COVID-19 period. US and EU refer to regional subsets. Models are based on Fama-French (3- and 5- Factor Models), Carhart (4-Factor Model), and extended specifications (Extended Six-Factor Model).

count how many variables are included in the model. This means a more complex model needs to explain more of the data to show real improvement. The six-factor model has the highest adjusted R-squared values in most cases, which shows that the extra factors help to explain returns better, not just add noise. The Carhart model, with fewer variables, still performs very well and provides a simpler alternative.

Table 4.5: Adjusted R-Squared during Russia-Ukraine War

Model	Momentum		Dividend		Volatility		Multifactor	
	US	EU	US	EU	US	EU	US	EU
3-Factor	0.7579	0.6784	0.8622	0.5398	0.7487	0.6114	0.7986	0.5443
4-Factor	0.7663	0.7230	0.8646	0.5411	0.7489	0.6113	0.7985	0.5444
5-Factor	0.7605	0.6815	0.8711	0.5412	0.7618	0.6111	0.8047	0.5445
6-Factor	0.7671	0.7294	0.8738	0.5423	0.7618	0.6109	0.8073	0.5446

Note: This table reports adjusted R-squared values for Smart Beta ETFs across various factor models during the Russia-Ukraine war period. US and EU refer to regional subsets. Models are based on Fama-French (3- and 5- Factor Models), Carhart (4-Factor Model), and extended specifications (Extended Six-Factor Model).

These results show that both models are strong and reliable choices for analyzing Smart Beta ETFs across different market conditions. However, the relatively high correlation between HML and CMA observed in the correlation matrix supports the decision to prioritize the Carhart four-factor model for the main analysis, as it reduces potential factor overlap while maintaining explanatory power. Together, these findings establish a strong basis for the subsequent analysis of Smart Beta ETF factor loadings. Accordingly, the Carhart four-factor model is employed for the primary analysis, and the extended six-factor model serves as a robustness check later in the thesis.

4.3 Findings

4.3.1 Factor Loading during COVID-19

The regression results for the COVID-19 period offer crucial insight into the behavior of factor exposures across regions and different Smart Beta ETFs. The analysis and all coefficient values discussed are based on the regression estimates reported in Table 4.6. Since the analysis investigates the factor loadings of Smart Beta ETFs specifically, it provides targeted evidence on how these rule-based investment strategies adjusted their exposures in response to the COVID-19 pandemic. By estimating a Carhart four-factor model that includes interaction terms with a COVID-19 indicator, the analysis captures not only the pre-pandemic baseline sensitivities of ETFs to risk factors, but also how these sensitivities changed during the pandemic period. These dynamics are particularly important for understanding the behavior of Smart Beta ETFs during a global health and economic shock that disrupted market functioning and investor behavior. This section systematically examines the observed changes in factor exposures across US and EU markets and across different ETF strategy categories. By focusing on both the cross-sectional differences and the within-pandemic shifts, it highlights how COVID-19 reshaped the risk profiles of Smart Beta ETFs.

During the COVID-19 period, the Market Risk Premium (MRP) remained the dominant driver of Smart Beta ETF returns across all types and regions of strategies, with consistently positive and statistically significant factor loadings. In the US, MRP exposures were notably high before the onset of the pandemic, especially for Momentum and Dividend ETFs, with coefficients close to one. For instance, the MRP loading for US Momentum ETFs was 0.9874, indicating an almost perfect correlation with market returns. Other US strategies, including Dividend and Multifactor ETFs, also showed only moderate increases in market sensitivity, with COVID interaction terms of approximately 0.10, reinforcing the view that US Smart Beta products were already strongly exposed to systemic market movements before the crisis began. In contrast, European ETFs, particularly those following dividend, volatility, and multifactor strategies, entered the crisis with substantially lower MRP loadings, ranging from just 0.45 to 0.64, compared to their US counterparts, which often exceeded 0.80. However, these same strategies experienced sharp increases in market sensitivity during the pandemic. For example, the COVID-period interaction terms for European Volatility and Dividend ETFs rose by 0.26 and 0.21 respectively, both statistically significant at the 1% level. These magnitudes suggest a marked shift in exposure.

Table 4.6: Carhart 4-Factor Model with COVID-19 Interactions for Smart Beta ETFs across US and EU

Term	**Momentum**		**Dividend**		**Volatility**		**Multifactor**	
	US	**EU**	**US**	**EU**	**US**	**EU**	**US**	**EU**
MRP	0.9874***	0.7127***	0.8596***	0.5877***	0.7112***	0.4477***	0.8100***	0.6400***
	(0.0516)	*(0.0124)*	*(0.0137)*	*(0.0213)*	*(0.0194)*	*(0.0286)*	*(0.0368)*	*(0.0497)*
ΔC–19 Intercept	-0.0005**	-0.0004**	-0.0002***	-0.0003***	-0.0006***	-0.0006***	-0.0003***	-0.0002**
	(0.0001)	*(0.0001)*	*(0.00005)*	*(0.00008)*	*(0.00008)*	*(0.00011)*	*(0.00005)*	*(0.00010)*
ΔC–19 × MRP	0.0019	0.1640***	0.1032***	0.2089***	0.1991***	0.2588***	0.1029***	0.1868***
	(0.0373)	*(0.0259)*	*(0.0123)*	*(0.0263)*	*(0.0272)*	*(0.0244)*	*(0.0234)*	*(0.0277)*
SMB	0.3875***	-0.4359***	0.1067**	-0.3703***	0.0927	-0.4544***	0.1770***	-0.1091*
	(0.0814)	*(0.0407)*	*(0.0484)*	*(0.0458)*	*(0.0864)*	*(0.0458)*	*(0.0630)*	*(0.0626)*
ΔC–19 × SMB	0.1162**	0.0394	-0.0470	0.1983***	0.1393**	0.2632***	0.0843**	0.0872
	(0.0443)	*(0.0173)*	*(0.0309)*	*(0.0667)*	*(0.0499)*	*(0.0765)*	*(0.0379)*	*(0.0629)*
HML	-0.0067	-0.1604***	0.3326***	0.1343***	0.1470***	-0.2618***	0.1904***	-0.0545
	(0.0877)	*(0.0056)*	*(0.0241)*	*(0.0338)*	*(0.0267)*	*(0.0188)*	*(0.0312)*	*(0.0408)*
ΔC–19 × HML	0.0861	0.0448	-0.0104	0.2314***	0.2092***	0.3991***	0.0611	0.2240***
	(0.0520)	*(0.1264)*	*(0.0353)*	*(0.0578)*	*(0.0488)*	*(0.0787)*	*(0.0379)*	*(0.0537)*
WML	0.2194***	0.3704***	-0.0900***	-0.0951***	-0.0010	0.0171	-0.0119	-0.0148
	(0.0318)	*(0.0432)*	*(0.0119)*	*(0.0149)*	*(0.0107)*	*(0.0168)*	*(0.0181)*	*(0.0135)*
ΔC–19 × WML	0.0995	-0.0932	-0.0444	0.0983***	0.1214**	0.1480**	0.0573	0.1204***
	(0.0664)	*(0.0679)*	*(0.0276)*	*(0.0355)*	*(0.0455)*	*(0.0654)*	*(0.0378)*	*(0.0379)*
Constant	-0.0002***	-0.0001*	-0.0001***	-0.00002**	-0.00002	0.0001***	-0.00006***	0.00009***
	(0.00002)	*(0.00003)*	*(0.00001)*	*(0.00001)*	*(0.00002)*	*(0.00001)*	*(0.00002)*	*(0.00001)*

Note: This table reports regression results from a Carhart four-factor model augmented with a COVID-19 interaction term. The model includes the following factors: MRP (Market Risk Premium), SMB (Small Minus Big), HML (High Minus Low), and WML (Winners Minus Losers, i.e., momentum). Interaction terms with a COVID dummy variable capture changes in factor sensitivity during the pandemic period. Results are reported separately for US and EU Smart Beta ETF categories (Momentum, Dividend, Volatility, Multifactor). Robust standard errors in italics and parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The data suggest that these lower beta profiles did not hold under extreme stress; instead, European strategies rapidly increased their sensitivity to the market as the crisis unfolded. In general, the analysis confirms that systemic shocks such as COVID-19 elevate the prominence of broad market risk, particularly for strategies and regions that are not already heavily exposed, and underscore the dynamic nature of factor sensitivities in periods of global disruption.

Regarding the size factor (SMB), the results reveal clear differences between the US and European Smart Beta ETF markets, both in terms of pre-pandemic exposures and shifts observed during the COVID-19 period. Before the crisis, US ETFs generally exhibited positive and significant loadings on the SMB factor, most notably within momentum and multifactor strategies. For example, US Momentum ETFs had a loading of approximately 0.39, suggesting an intentional tilt toward small-cap stocks. Multifactor strategies followed a similar pattern, although with more moderate exposure. In contrast, European ETFs consistently displayed negative SMB loadings across most strategy categories. Momentum ETFs in Europe showed a particularly strong large-cap orientation, with a significant negative coefficient of about -0.44. Dividend and volatility strategies in the EU also leaned heavily toward large-cap stocks, with SMB loadings of roughly -0.37 and -0.45, respectively. These findings reflect a structural tendency within European ETF construction to emphasize larger, more established firms. Such preferences may arise, along with the reaction to crisis conditions, from market composition, lower small-cap liquidity, and a generally more conservative investor base. What is especially notable is how these exposures evolved during the COVID-19 pandemic. Although US strategies maintained or slightly increased their small-cap tilt, European ETFs, particularly in the dividend and volatility categories, exhibited statistically significant positive shifts in SMB loading. EU Volatility ETFs saw an increase of 0.26 in their SMB loading, and EU Dividend ETFs shifted upward by about 0.20, both of which are economically meaningful and statistically significant. These changes suggest that even in a region structurally oriented toward large-cap equities, there was a degree of tactical rotation toward smaller firms during the crisis. This could reflect either a rebound effect, as small caps recovered faster from the initial shock, or a deliberate attempt to capture higher-risk, higher-reward segments in an environment of extreme uncertainty. In the US, changes during the pandemic were less dramatic, but still present. In general, the SMB analysis highlights persistent structural differences in ETF construction and investor preferences between the US and Europe. At the same time, it also reveals that the COVID-19 crisis triggered dynamic shifts, especially in European ETFs, where even traditionally large-cap-focused strategies temporarily moved toward smaller-cap exposures.

Examining the value factor (HML) yields a more differentiated set of results, particularly when comparing regional and strategic patterns before and during the COVID-19 period. Prior to the crisis, US Dividend ETFs displayed strong and statistically significant positive exposures to HML, consistent with their focus on mature, high-dividend firms that often score high on traditional value metrics. Compared to the other category groups, momentum and volatility strategies tend to have weak or even neutral HML exposures. These findings are in line with expectations, since strategies oriented around price momentum or low volatility typically do not prioritize valuation-based selection criteria. In contrast, European ETFs showed a more mixed relationship with the value factor. Only Dividend ETFs in the EU had a notable and significant positive HML loading prior to the pandemic. Other categories, particularly Momentum and Volatility ETFs, displayed negative or insignificant exposures, suggesting a weaker alignment with value-based investing principles. For example, the HML loading for European Volatility ETFs was significantly negative, around -0.26, highlighting a preference for stocks with growth-like characteristics. COVID-19 triggered notable shifts in value exposures, especially in Europe. The HML interaction terms reveal that European Dividend and Volatility ETFs significantly increased their value exposure during the pandemic. EU Volatility strategies saw their HML loading rise by approximately 0.31, while EU Multifactor ETFs also experienced a meaningful increase of around 0.22. In the US, the changes were present as well. Dividend ETFs showed an increase in HML exposure of approximately 0.23, suggesting a slight reinforcement of value orientation during the crisis, while other strategy types only exhibited little change. The general stability in US HML exposures may reflect a structural embedding of value characteristics in the design of US Smart Beta ETFs, particularly in income-oriented and diversified strategies. Taken together, the analysis of HML loadings highlights that while value exposure was generally stronger and more persistent in US strategies, the COVID-19 period saw European ETFs, especially in volatility and multifactor categories, moving more decisively toward value stocks. As such, the crisis appears to have temporarily strengthened the relevance of the value factor, particularly in European contexts where it had previously played a less central role.

The analysis of the momentum factor (WML) reveals patterns that are largely consistent with expectations based on ETF design, but also exposes some noteworthy shifts during the COVID-19 period. Unsurprisingly, Momentum ETFs exhibited strong and statistically significant positive exposures to the WML factor in both regions, reaffirming that these strategies effectively captured recent performance trends. US Momentum ETFs showed particularly high sensitivity, with pre-crisis loadings exceeding 0.22, while their European counterparts also demonstrated positive and significant exposures, although somewhat lower. These findings confirm that Smart Beta ETFs explicitly built to harness momentum characteristics performed in line with their strategic mandate during the pandemic. However, the COVID-19 interaction terms suggest that even these ETFs were not entirely static in their behavior. While US Momentum strategies saw only a minor and statistically insignificant shift, European Momentum ETFs experienced a modest decrease in WML loading, indicating a slight dampening of pure momentum exposure under crisis conditions. This could reflect temporary distortions in return patterns or increased overlap with other defensive characteristics that emerged during the market shock. Outside of dedicated momentum products, the relationship with WML was more heterogeneous. Dividend ETFs in the US exhibited a significantly negative pre-crisis loading of about -0.09, which aligns with their preference for stable, income-generating firms that typically do not fall into the category of recent outperformers. Interestingly, the COVID-19 period brought a modest positive shift in momentum exposure for European Dividend ETFs, with a statistically significant interaction effect of roughly 0.10. Volatility and Multifactor ETFs presented weaker and more varied connections to the momentum factor. In Europe, Volatility ETFs had a small but positive and statistically significant WML loading pre-crisis, which increased slightly during the pandemic. These results reflect the blended nature of these strategies, which may pick up partial momentum exposure without explicitly targeting it. Overall, the analysis underscores the robustness of momentum exposure in dedicated strategies, especially in the US, while also revealing that other ETF types selectively increased their alignment with momentum during the crisis. These shifts suggest that even within structured rule-based products, dynamic rebalancing or market-driven factor drift can subtly alter exposure profiles in response to extreme market conditions like those triggered by COVID-19.

Regional comparisons reveal that US Smart Beta ETFs maintained more stable and consistent factor exposures than their European counterparts, particularly during the COVID-19 period. In the US, factor loadings for market and momentum exposures were robust and statistically significant across nearly all strategy categories. This consistency was especially pronounced in Momentum and Multifactor ETFs, which remained closely aligned with their intended factor targets. In contrast, European Smart Beta ETFs showed greater variability and generally weaker factor loadings, especially for the size (SMB) and value (HML) factors. Momentum and Volatility ETFs in Europe, for instance, exhibited clearly negative and statistically significant size loadings of around -0.40, indicating a strong tilt toward large-cap stocks. Similarly, value exposures in European Dividend ETFs were less consistent and often not statistically significant, suggesting weaker alignment with value characteristics. Across categories, factor loadings in European ETFs tended to fluctuate more and show less consistency over time, whereas US ETFs maintained more consistent and more coherent exposure patterns. These observations point to different behavioral patterns in how factor strategies operated between regions during the pandemic. Although US smart beta products adhered largely to their strategic factor definitions with measurable consistency, European ETFs showed more fluid and less predictable exposure profiles throughout the COVID-19 period.

The statistical reliability of the estimated factor loadings appears to be strong across the regression results. Standard errors were generally low, particularly in the US sample, indicating that the coefficient estimates are precise and unlikely to be driven by random variation. The most influential factors, notably the Market Risk Premium (MRP) and the momentum factor (WML), were statistically significant at the 1% level in nearly all ETF categories. This reinforces the view that these exposures were not only quantitatively large but also robust from a statistical standpoint. The WML factor demonstrated especially consistent and significant loadings for Momentum ETFs, which aligns well with the theoretical construction of these products. Similarly, MRP loadings were highly significant across the board, confirming the dominant role of market risk in explaining return variation during the COVID-19 period. What strengthens the credibility of these findings is the alignment between statistical outcomes and the behavior of expected factors. Momentum ETFs, for instance, showed strong positive exposure to WML, while all ETF categories retained a high and significant sensitivity to MRP. This congruence between empirical results and theoretical expectations supports the overall validity of the model and the conclusions drawn from it.

In conclusion, the COVID-19 period confirmed that the market risk premium was the most influential and consistently significant factor in explaining the returns of the Smart Beta ETF returns across both the US and the European markets. Momentum and size also played an important role, especially in the US, where factor loadings were more stable and statistically robust. In contrast, European ETFs showed more variability and generally weaker exposures, particularly to size and value factors, reflecting distinct patterns in factor alignment across regions. Dividend ETFs consistently exhibited positive value exposures and Momentum ETFs maintained strong and statistically significant momentum loadings, both of which correspond closely with the strategic objectives of these products. Although factor exposure profiles remained largely aligned with ETF design intentions, the COVID-19 shock introduced notable shifts, particularly in Europe. There, strategies that had previously shown more conservative or muted factor sensitivities adjusted more dynamically during the crisis, increasing their exposure to market and value factors. Overall, the Carhart four-factor model effectively accounted for the majority of variation in ETF returns during the pandemic, indicating that traditional factors remained highly relevant even under systemic market stress. At the same time, observed regional differences in exposure levels and crisis-driven shifts underscore the importance of ETF construction choices, market structure, and local investment practices in shaping how Smart Beta strategies react during periods of extreme market disruption.

4.3.2 Factor Loading during the Russia-Ukraine War

The regression estimates summarized in Table 4.7 provide information on how the Smart Beta ETF factor exposures evolved in response to the Russia-Ukraine war, covering the first ten months of the conflict. Using the same methodology as for the COVID-19 period, this section analyzes the behavior of factor loadings across regional markets and strategy types.

During the Russia-Ukraine war, the MRP remained the most influential factor across all categories and regions of Smart Beta ETFs. In the US, pre-war MRP coefficients were uniformly high and statistically robust, with values approaching or exceeding 0.90 across strategies. For instance, the MRP loading for US Momentum ETFs was 0.9859, while Volatility and Multifactor ETFs recorded coefficients of 0.8078 and 0.8505, respectively. These pre-conflict values indicate a strong dependence on overall market movements, even in strategies that do not explicitly track the broad index. European ETFs also exhibited positive and significant pre-war MRP loadings, although at somewhat lower levels.

Interaction terms capturing within-war shifts in MRP exposure showed notable regional asymmetries. US Momentum ETFs experienced a statistically significant increase in MRP loading of 0.0942, indicating an increased sensitivity to market movements during the war. In contrast, several European strategies exhibited negative and significant changes. EU Momentum declined by -0.1046, EU Volatility by -0.1127, and EU Multifactor by -0.0449. These reductions suggest that some European ETFs adjusted their exposure to reduce market-linked volatility during the conflict period. Taken together, the results confirm that MRP remained the central driver of Smart Beta ETF returns during the early months of the Russia-Ukraine war. US ETFs continued to show strong and even increased market sensitivity, while many European ETFs exhibited a decline in exposure, reflecting differentiated responses to geopolitical instability.

The size factor displayed persistent and regionally distinct patterns during the Russia-Ukraine War, reflecting differences in Smart Beta ETF design and behavior under geopolitical stress. In the US, pre-war SMB loadings were positive in most strategy categories, consistent with a general tilt toward small-cap stocks. For example, US Momentum ETFs recorded a statistically significant coefficient of 0.4018, suggesting a pronounced small-cap orientation. Dividend ETFs had a smaller but still positive value of 0.1074. US Volatility ETFs, in contrast, only showed a near-zero loading of 0.1066.

Table 4.7: Carhart 4-Factor Model with Russia-Ukraine War Interactions for Smart Beta ETFs across US and EU

Term	**Momentum**		**Dividend**		**Volatility**		**Multifactor**	
	US	**EU**	**US**	**EU**	**US**	**EU**	**US**	**EU**
MRP	0.9859***	0.7874***	0.8848***	0.6526***	0.8078***	0.5453***	0.8505***	0.6926***
	(0.0438)	*(0.0119)*	*(0.0129)*	*(0.0197)*	*(0.0172)*	*(0.0305)*	*(0.0326)*	*(0.0493)*
War Intercept	-0.0000	-0.0001	0.0002***	-0.0002***	0.0002***	-0.0002***	0.0001**	-0.0002***
	(0.0001)	*(0.0001)*	*(0.00004)*	*(0.00005)*	*(0.00005)*	*(0.00007)*	*(0.00004)*	*(0.00005)*
War × MRP	0.0942***	-0.1046**	0.0021	-0.1117***	-0.0798***	-0.1127***	0.0161	-0.0449*
	(0.0245)	*(0.0228)*	*(0.0140)*	*(0.0241)*	*(0.0251)*	*(0.0339)*	*(0.0191)*	*(0.0232)*
SMB	0.4017***	-0.4357***	0.1074**	-0.2953***	0.1066	-0.3509***	0.1915***	-0.0602
	(0.0853)	*(0.0434)*	*(0.0495)*	*(0.0468)*	*(0.0896)*	*(0.0542)*	*(0.0662)*	*(0.0632)*
War × SMB	0.1565*	0.0300	-0.0547*	-0.0110	-0.0626	-0.1173	-0.0417	-0.1417***
	(0.0801)	*(0.0345)*	*(0.0283)*	*(0.0570)*	*(0.0660)*	*(0.0694)*	*(0.0251)*	*(0.0517)*
HML	-0.0230	-0.1143**	0.3294***	0.1442***	0.2054***	-0.1739***	0.2086***	-0.0290
	(0.0919)	*(0.0265)*	*(0.0225)*	*(0.0331)*	*(0.0272)*	*(0.0257)*	*(0.0331)*	*(0.0366)*
War × HML	0.0451	-0.0680**	0.0561***	0.0380	-0.0749***	-0.0389	0.0211	0.0404
	(0.0447)	*(0.0128)*	*(0.0167)*	*(0.0314)*	*(0.0227)*	*(0.0616)*	*(0.0194)*	*(0.0328)*
WML	0.2064***	0.3082***	-0.1029***	-0.1184***	-0.0144	0.0093	-0.0114	-0.0221
	(0.0277)	*(0.0391)*	*(0.0121)*	*(0.0163)*	*(0.0133)*	*(0.0156)*	*(0.0194)*	*(0.0134)*
War × WML	0.1417**	0.0664**	0.0153	0.0489*	0.0409**	-0.0258	0.0076	-0.0062
	(0.0565)	*(0.0141)*	*(0.0178)*	*(0.0277)*	*(0.0183)*	*(0.0543)*	*(0.0114)*	*(0.0284)*
Constant	-0.0003***	-0.0001***	-0.0001***	-0.00004***	-0.0001***	0.00003***	-0.0001***	0.00007***
	(0.0000)	*(0.0000)*	*(0.00001)*	*(0.00001)*	*(0.00002)*	*(0.00001)*	*(0.00002)*	*(0.00001)*

Note: This table reports regression results from a Carhart four-factor model augmented with a Russia-Ukraine war interaction term. The model includes MRP (Market Risk Premium), SMB (Small Minus Big), HML (High Minus Low), and WML (Winners Minus Losers, i.e., momentum). Interaction terms with a war dummy variable capture changes in factor sensitivity during the war period. Results are reported separately for US and EU Smart Beta ETF categories (Momentum, Dividend, Volatility, Multifactor). Robust standard errors in italics and parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

European ETFs continued to show a reverse pattern. Momentum strategies exhibited a strong and significantly negative SMB coefficient of -0.4357, indicating a clear preference for large-cap stocks. Similar negative exposures appeared in EU Volatility (-0.3509) and a small, near-zero value in EU Dividend ETFs. Interaction terms reflecting within-war shifts in size exposure reveal further differences. US Momentum ETFs experienced a statistically significant increase of 0.1565 in SMB loading, implying an even stronger tilt toward smaller-cap stocks during the war period. Other US strategies showed less pronounced or insignificant changes. In Europe, the most notable shift occurred in Multifactor ETFs, which registered a statistically significant decline of -0.1417 in SMB loading, reflecting an even stronger tilt toward large caps. The EU Volatility ETFs also recorded a negative change (-0.1173), while the changes in other categories were smaller or not statistically significant. Together, these results suggest that regional preferences in size exposure were largely maintained during the conflict, but with some tactical adjustments. US ETFs remained more consistently exposed to smaller firms, while European ETFs continued to lean toward large-cap holdings and, in some cases, deepened that tilt.

The HML factor displayed varied and strategy-specific patterns during the Russia-Ukraine War period, reflecting differing approaches to valuation across ETF types and regions. As expected, Dividend ETFs showed the strongest and most consistent exposure to the value factor. In the US, the pre-war HML loading for Dividend ETFs was 0.3294 and highly significant, while in the EU the value was 0.2054. Other categories of Smart Beta ETF categories revealed weaker or even negative value exposures. European Momentum ETFs recorded a significantly negative HML coefficient of -0.1143, indicating a clear preference for growth-oriented stocks. Similarly, EU Volatility ETFs had a strongly negative loading of -0.1739. These pre-war values suggest a broad avoidance of value characteristics in certain European strategies. In contrast, the multifactor US ETFs maintained a significantly positive HML loading of 0.2086, consistent with a balanced exposure to value across multiple factors. The terms of the within-war interaction highlight further variation. US Dividend ETFs experienced a modest increase in HML exposure of 0.0561, suggesting a strengthened value orientation during the conflict. Meanwhile, US Volatility ETFs saw a significant decrease of -0.0749 in HML loading, implying a retreat from value stocks in favor of potentially more defensive characteristics. In Europe, war-related changes in HML were less consistent. EU Momentum ETFs showed a small negative shift (-0.0680), while the changes in other strategies were statistically insignificant or modest in magnitude. Taken together, the results point to a continued and even strengthened value orientation in dividend strategies during the war, while other categories, especially in Europe, maintained or deepened their tilt away from value. The data suggest that the value exposure remained highly dependent on the type of strategy, with dividend-focused

ETFs being the most stable carriers of value characteristics during the conflict period.

Momentum ETFs demonstrated the strongest and most consistent positive exposures to the WML (momentum) factor during the Russia-Ukraine War. In both the US and Europe, pre-war WML loadings were high and statistically significant, reflecting these ETFs' explicit strategy of capturing recent winners. The exposures confirm that the Momentum ETFs retained their alignment with short-term performance trends throughout the conflict period, which is entirely consistent with their design and expected behavior. In contrast, Dividend ETFs continued to display weak or negative momentum exposure. The WML coefficient for US Dividend ETFs was -0.1029. European Dividend ETFs showed a near-zero loading, consistent with a neutral momentum position. This behavior aligns with the long-term valuation-based orientation of dividend strategies, which typically do not prioritize recent performance. Volatility and Multifactor ETFs showed more moderate and mixed momentum exposures. While US Volatility and Multifactor strategies had small negative pre-war WML loadings, their European equivalents were slightly positive, though generally not statistically significant. These muted results likely reflect the broader diversification of these ETF designs, which may indirectly capture some momentum exposure through overlapping characteristics but do not explicitly target the factor. Interaction terms capturing within-war shifts reveal that US Momentum ETFs further increased their WML exposure by 0.1417, a statistically significant change. EU Momentum ETFs also recorded a positive and significant shift of 0.0664. These results suggest that even during periods of geopolitical tension, momentum strategies not only maintained, but strengthened their alignment with recent performance trends. Other types of strategy showed smaller and mostly insignificant changes. In general, the results reaffirm the resilience of the momentum factor in ETFs explicitly designed to track it. Momentum ETFs remained highly consistent in their exposure to WML, with some strategies even amplifying this exposure during the war. Meanwhile, Dividend, Volatility, and Multifactor ETFs continued to display more varied and muted connections to momentum.

The statistical robustness of the regression results further reinforces confidence in the findings. Standard errors across key coefficients were generally low, indicating that the estimated values are precise and are not overly influenced by noise. Most of the main factor loadings, such as MRP and WML for momentum ETFs, and SMB to identify regional size differences, were statistically significant at the 1% level. The coefficients capturing shifts during the Russia-Ukraine War period were also reliable. The interaction terms for several strategies, particularly US Momentum (WML) and EU Volatility (MRP), demonstrated statistical significance and were consistent with the expected behavioral adjustments under geopolitical stress. These results confirm that changes in factor sensitivities during the conflict were not random but reflect meaningful strategic responses in the behavior of Smart Beta ETFs. This combination of statistical precision and significance supports the reliability of the analysis and aligns well with the expected behavior of rule-based Smart Beta strategies under systemic stress. The results make sense in light of both the theory and the design of ETFs, which confirms the robustness of the factor-based framework used in this context.

In summary, analysis of Smart Beta ETF factor loadings during the Russia-Ukraine War reveals that traditional risk factors remained highly explanatory, with the Market Risk Premium continuing to dominate return variation across regions and strategies. Although core exposures were largely aligned with ETF design intentions, several significant shifts, particularly in momentum and size, demonstrated that Smart Beta strategies are not static, but adapt to geopolitical shocks in differentiated ways. Regional contrasts, especially between US and European ETFs, were consistent and robust, highlighting both structural design choices and strategic responses to elevated uncertainty. These findings underscore the resilience of factor-based investments, even in the face of geopolitical disruption.

4.3.3 Crisis Analysis and Exposure Patterns

This comparative section focuses on the contrast between the behavior of Smart Beta ETFs during the COVID-19 pandemic and the Russia-Ukraine war, building on the separate empirical findings already discussed earlier. Rather than repeating detailed factor analyzes, the goal here is to synthesize key differences and highlight dynamics across both periods. A critical similarity observed in both crises is the dominance of the Market Risk Premium (MRP) as a return driver, with US ETFs consistently showing strong exposure. However, European ETFs showed markedly different behavior. During COVID-19, they increased MRP loadings even in defensive strategies, suggesting a breakdown in factor orthogonality under global systemic stress. In contrast, during the Russia-Ukraine War, European ETFs deliberately reduced their MRP sensitivity, indicating a move toward derisking and regional insulation. This contrast underscores how the scope and origin of a crisis (global vs. regional) shape ETF reactions. Another divergence emerged in the behavior of the size factor (SMB). Although US ETFs maintained a steady small-cap tilt in both periods, European ETFs shifted directionally: COVID-19 prompted an unusual increase in small-cap exposure, likely in pursuit of rebound opportunities, while the war triggered a return to large-cap holdings. This "crisis flip" in size exposure is particularly notable, suggesting that European ETF strategies can be repositioned rapidly even when their long-term design leans large-cap. For the value factor (HML), consistent exposures were observed only within the dividend ETFs. Outside of these, the contrast was sharp:

COVID-19 led to a value rotation in Europe as investors sought fundamentals in recovery plays. However, the Russia-Ukraine war saw little movement or even retreat from value exposures. This may reflect the different investor priorities in each crisis: stability and defensiveness during geopolitical unrest versus opportunism and recovery during a systemic shock. Momentum (WML) remained the most predictable factor. Dedicated Momentum ETFs in both the US and Europe maintained strong factor loadings during both crises, with increases observed during the Russia-Ukraine war. A notable and somewhat unexpected observation was the weakening of momentum signals in Europe during the COVID-19 period, which may be attributed to extreme price fluctuations disrupting standard momentum trends. Additionally, a structural pattern becomes evident, as US ETFs showed greater consistency and strategic discipline across the crises, while European ETFs responded more tactically, especially during the pandemic. This distinction probably reflects both the maturity of the ETF market and the differences in regional investment philosophy.

In summary, while both crises activated dynamic shifts in Smart Beta ETF behavior, the COVID-19 pandemic triggered broader systemic factor realignment, whereas the RussiaUkraine War elicited more selective, regionally driven adjustments. The divergence in European behavior between the two events is particularly revealing of how ETF exposure can flex under different types of external stress.

4.4 Robustness Check

To assess the robustness of our baseline results, we extend the Carhart four-factor model by incorporating the profitability (RMW) and investment (CMA) factors, yielding a six-factor specification. This extension serves to verify whether the initial findings are stable when a broader set of systematic risk sources is considered. Overall, the six-factor model confirms the general patterns observed previously, yet introduces several meaningful differences in magnitude, significance, and interpretation that provide a more nuanced understanding of ETF factor behavior during the COVID-19 crisis and the Russia-Ukraine war.

On the positive side, the six-factor model strengthens and expands many of the previous findings. The interaction terms between the COVID-19 dummy and the MRP increase both in magnitude and significance across almost all strategies, particularly within the EU. This suggests that the market sensitivity of Smart Beta ETFs was even more affected during the pandemic than initially indicated by the simpler specification and that some of this variation was previously absorbed by omitted factor effects. Additionally, the role of momentum is reinforced, with more consistently significant crisis interaction terms, especially for Volatility and Multifactor ETFs. Crucially, the inclusion of RMW and CMA uncovers new patterns. The RMW interaction term during COVID-19 is significantly negative for US Dividend ETFs, indicating that strategies tilted toward profitable firms were more vulnerable during the earnings uncertainty of the pandemic. Similarly, the strong and positive CMA effect for EU Momentum ETFs during the COVID-19 crisis highlights a previously overlooked shift in investor preference toward more conservative investment strategies in response to heightened macroeconomic risk. However, the expanded model also presents drawbacks. The inclusion of additional factors slightly reduces the clarity of some previously strong effects, particularly in SMB and HML interactions, which lose significance or stability across specifications. An explanation for this is the high degree of multicollinearity between HML and CMA observed in the correlation matrix (Table 4.3), where the pairwise correlation reached 0.7205. Such a strong linear relationship implies that the two variables may capture overlapping information, which can distort coefficient estimates and inflate standard errors. As a result, the addition of CMA appears to dilute the interpretive clarity of the traditional value factor, potentially obscuring rather than improving the understanding of style-based exposures. Moreover, while RMW and CMA improve model completeness, their coefficients are not uniformly significant or stable across all strategy and region combinations, suggesting that their relevance may be context dependent rather than universally robust.

During the Russia-Ukraine war, the MRP continues to dominate as the key driver of ETF returns, but COVID-19-like asymmetries between US and EU exposures become more pronounced. For example, the war-period decline in MRP exposure among EU Momentum ETFs becomes even more significant (-0.1200) compared to the Carhart model (-0.1046). Similarly, the drop in EU Multifactor ETFs' MRP loading is slightly stronger, reinforcing the interpretation that European ETFs reduced market sensitivity in response to the war, even after controlling for profitability and investment. On the US side, the interaction term for MRP remains positive and significant for Momentum. The introduction of RMW and CMA reshapes several exposure patterns. Both factors emerge as significant in a number of strategies, with RMW particularly relevant for EU Dividend (-0.2932) and Volatility (-0.3381) ETFs, and CMA significantly affecting EU Momentum (-0.1700) and EU Dividend (-0.1351) exposures. At the same time, the WML factor retains its central role in Momentum ETFs, with coefficients remaining positive and highly significant in both the US and the EU. More importantly, the war-interaction terms for WML remain robust and significant in the extended model. US Momentum ETFs increase the exposure by 0.1493 and the EU Momentum by 0.0819, indicating that momentum strategies not only preserved their behavior but intensified it during the war. This contrasts with dividend strategies, where WML effects remain negligible. Meanwhile, previously strong effects such as HML and SMB become more muted or unstable. This is particularly evident in Dividend and Multifactor strategies, where HML interaction terms decline in size or significance. The strong correlation between HML and CMA (0.7205) likely contributes to this instability by introducing multicollinearity, which complicates the clear attribution of value-related effects. Similarly, the SMB interaction coefficients fluctuate and lose strength in some strategies, although some remain significant, such as the decline in the EU Multifactor. In general, the six-factor specification enriches the interpretation of the behavior of ETFs under geopolitical stress, confirming the main Carhart results and highlighting the unique contribution of profitability and investment factors.

In summary, the six-factor model supports the robustness of the original findings for both the COVID-19 and Russia-Ukraine war periods, while revealing additional factor sensitivities specific to profitability and investment behavior. In both crises, the introduction of RMW and CMA provided more granularity, particularly for European ETFs where these new factors played a more prominent role. For COVID-19, these factors clarified latent exposure shifts, such as a stronger preference for conservative investment strategies and a reduced sensitivity to profitability in uncertain conditions. During the war period, the same factors confirmed these tendencies, especially in EU Dividend and Volatility ETFs. At the same time, momentum emerged as consistently robust across both crises, particularly for Momentum ETFs, where exposure not only remained significant but intensified in both regions. Although the inclusion of RMW and CMA introduced some multicollinearity, especially affecting the clarity of HML coefficients due to their strong correlation, the overall factor structure remained stable. Thus, Smart Beta ETFs were shown to retain their design-aligned exposures while adapting in strategic and regionally differentiated ways to systemic shocks. The six-factor model affirms that the observed shifts were meaningful and robust across different types of geopolitical and macroeconomic uncertainty.

4.5 Performance Analysis of Smart Beta ETFs

To evaluate the performance of smart beta strategies in varying market environments, this section analyses three key risk-adjusted return measures: the Sharpe ratio, the Sortino ratio, and the Information ratio. These metrics offer a detailed perspective on portfolio performance. The Sharpe ratio covers excess return per unit of total risk, the Sortino ratio refines this by considering only downside volatility, and the Information ratio evaluates returns relative to a benchmark, accounting for the tracking error. For this study, both factor-specific benchmarks and broad market indices serve as reference points for the Information ratio, allowing for an assessment of both targeted and general outperformance.

4.5.1 Annualized Performance Ratios

Across the 24 result scenarios, formed by different factors, regions and periods, Smart Beta ETFs outperformed their respective benchmarks in 37.5% of the Sharpe ratios. Also, the Sortino ratio does not show a different picture, with an outperformance in 33.3% of the cases. These results in Table 4.8 indicate a limited and inconsistent advantage in risk-adjusted performance relative to the factor-specific benchmark constructs. Although smart beta strategies offer structured exposure to known risk premia, their realized outcomes relative to benchmarks, especially during periods of stress, appear far from good. The variety of factor configurations in the sample shows that smart beta portfolios are designed to be flexible, but the results suggest that this flexibility does not consistently lead to better performance compared to their benchmarks. Clear regional symmetries emerge from the data as well. US smart beta portfolios outperformed their benchmarks in 33.3% of Sharpe and Sortino ratios. EU portfolios matched this 33.3% outperformance rate, contradicting earlier assumptions that US implementations are generally better. Since the benchmarks are factor-specific indices rather than general market indices, these ratios somehow show the ability of the Smart Beta ETFs to track and outperform their underlying index. Therefore, the underperformance in both regions likely reflects inefficiencies in smart beta index design or ETF tracking quality, rather than market-level conditions.

The performance of smart beta portfolios varied considerably across regimes and between factor-specific implementations as well. The pre-crisis period from January 2015 to January 2020 ensures complete data coverage for all benchmarks. Still, only 3 out of 8 Sharpe ratios outperformed the benchmark in this period. Notable exceptions included the Multifactor EU portfolio, which recorded a factor-specific Information ratio of 0.3372, and Dividend EU with a moderately positive 0.1219. In contrast, Multifactor US showed a negative Information ratio of -0.6467, while Momentum US and Volatility EU also showed particularly poor performance, with Information ratios of -1.0350 and -0.5540.

During the COVID period from February to December 2020, conditions were far more volatile. 4 out of 8 Smart Beta Sharpe ratios exceeded those of the factor-specific benchmarks, although they are mostly negative. Momentum US achieved a strong absolute performance in the market with a Sharpe ratio of 0.6012, but its Information ratio of -0.0320 suggested only marginal tracking advantage. Dividend EU and Volatility US, however, posted comparatively strong Information ratios of 0.3189 and 0.2163. At the same time, considerable underperformance happened in other segments, most notably Multifactor US, which registered a deeply negative Information ratio of -1.2946, and Momentum EU at -0.4821.

Table 4.8: Annualized Performance Metrics: SB Portfolios vs. Benchmark and Market

Asset	**Period**	**Sharpe Ratio**		**Sortino Ratio**		**IR**	
		SB	**Bench.**	**SB**	**Bench.**	**SB**	**Mkt.**
Momentum US	Pre-Crisis	0.3969	0.7852	0.3568	0.7037	-1.0350	-0.4359
	COVID	0.6012	0.6095	0.4991	0.5212	-0.0320	0.6390
	WAR	-0.2431	-0.2966	-0.2353	-0.2818	0.1314	0.8236
Momentum EU	Pre-Crisis	0.3679	0.5530	0.3330	0.4988	-0.1642	0.4521
	COVID	0.1655	0.4769	0.1374	0.4129	-0.4821	0.6792
	WAR	-0.4581	-0.4336	-0.4413	-0.4294	0.0671	0.0247
Dividend US	Pre-Crisis	0.3837	0.3627	0.3576	0.3363	0.0156	-0.1812
	COVID	-0.0708	-0.2097	-0.0649	-0.1999	0.0950	-0.3143
	WAR	-0.3432	-0.0939	-0.3453	-0.0936	-0.1829	0.1864
Dividend EU	Pre-Crisis	0.1128	0.0217	0.1014	0.0194	0.1219	-0.1839
	COVID	-0.3735	-0.5157	-0.3253	-0.4164	0.3189	-1.0864
	WAR	-0.7666	-0.6107	-0.7492	-0.6286	-0.2408	-0.7850
Volatility US	Pre-Crisis	0.6143	0.7026	0.5579	0.6486	-0.3256	-0.2372
	COVID	-0.1321	-0.2064	-0.1121	-0.1859	0.2163	-1.8847
	WAR	-0.2104	0.0766	-0.2093	0.0728	-0.6883	0.9610
Volatility EU	Pre-Crisis	0.4481	0.6170	0.4116	0.5679	-0.5540	0.2412
	COVID	-0.3716	-0.2600	-0.2977	-0.2105	-0.0980	-0.4980
	WAR	-0.6531	-0.6422	-0.6817	-0.6436	0.2251	-0.1109
Multifactor US	Pre-Crisis	0.4175	0.5804	0.3840	0.5380	-0.6467	-
	COVID	0.0755	0.4523	0.0650	0.3908	-1.2946	-
	WAR	-0.3575	-0.5217	-0.3592	-0.5413	0.7469	-
Multifactor EU	Pre-Crisis	0.4384	0.1502	0.3901	0.1367	0.3372	-
	COVID	-0.0062	-0.0916	-0.0051	-0.0781	0.3092	-
	WAR	-0.7838	-0.4445	-0.7560	-0.4371	-0.9992	-

Note: This table reports annualized Sharpe, Sortino, and Information ratios for Smart Beta ETFs and their respective benchmarks and market indices (S&P 500 for US assets, Euro Stoxx 600 for EU assets) across three periods: Pre-Crisis (Jan 2015-Jan 2020), COVID (Feb-Dec 2020), and WAR (Feb-Dec 2022). IR is reported for SB ETFs relative to both the factor benchmark and the broader market.

In the Russia-Ukraine war period from February to December 2022, the relative performance of Smart Beta ETFs deteriorated even more visibly. Only 2 out of 8 Sharpe ratios indicated benchmark outperformance, and most of the portfolios delivered negative Sharpe and Sortino ratios. Information ratios continued their decline, with Multifactor EU reaching -0.9992 and Volatility US falling to -0.6883. Nonetheless, some limited resilience was observable in isolated cases, such as Momentum US, which managed a slightly positive Information ratio of 0.1314, and Dividend US, which closed the period at -0.1829.

The Information ratio reveals structural weaknesses in Smart Beta portfolios. With the inclusion of IR values for the market benchmarks (S&P 500 and Euro Stoxx 600), we extend the evaluation of tracking abilities by focusing on market outperformance. When benchmarked against broad market indices rather than factor-specific indices, Smart Beta ETFs show a mixed picture. During the pre-crisis period, the majority of Smart Beta ETFs lagged behind the broader market. Interestingly, US Volatility underperformed with an Information ratio of -0.2372, while the European counterpart posted a market IR of 0.2412. In the COVID period, Momentum US outperformed the market with an IR at 0.6390, showing, alongside their US counterpart and Multifactor EU, a strong performance. But, on the other hand, most of the other Smart Beta categories exhibited highly negative values close to minus 1.

Taking the different ratios into consideration, we get a mixed picture. Although Smart Beta ETFs may perform worse than the benchmark they try to track, they still can outperform the market significantly. Of course, this can also happen the other way round: Volatility US offered a surprising IR of 0.2163, which appears strong until contrasted with the sharply negative market IR of -1.8847. Also, shifts in regime-behavior are not unusual. Multifactor US underperformed in the pre-crisis period and during COVID. This changes during the Russia-Ukraine war period, where suddenly an IR of 0.7469 shows clear outperformance. The exact opposite picture is visible in the European market for the same factor ETF. Volatility US undermines the fact that there is no real pattern in behavior. During the Russia-Ukraine war, it registered a factor-specific IR of -0.6883, whereas the broader market IR reached 0.9610. This represents a total flip from the COVID period, where Volatility US managed to outperform the factor-specific IR but underperformed the market IR.

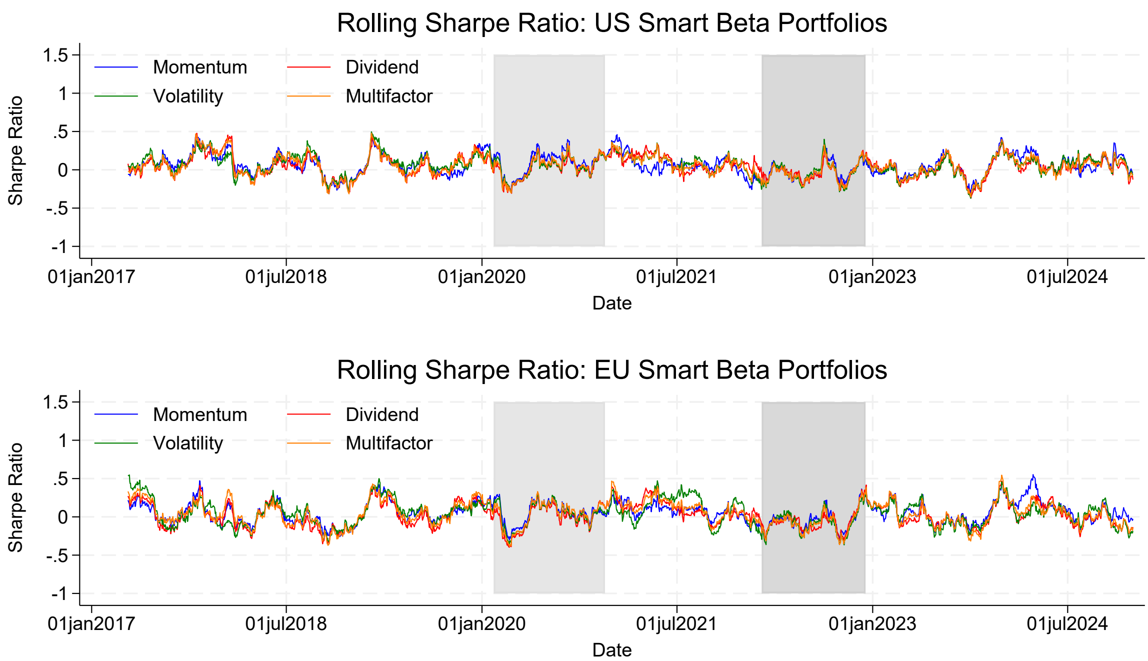
In summary, most Smart Beta ETFs struggle to effectively track their underlying factor-specific benchmark and only show outperformance in 37% of the Sharpe ratio scenarios. A little better is the performance compared to the broad market indices (S&P 500 and Euro STOXX 600), although 11 out of 24 IR ratios still fall below the 50% mark. This shows that more than half of the Smart Beta portfolios fail to outperform the broad market. When considering the specific crisis behavior, both Momentum Smart Beta ETFs showed strong relative performance to the market during those stress periods. Lastly, during the Russia-Ukraine war, a negative effect is visible in all EU Smart Beta categories, showing a negative market IR. On the other hand, the US categories performed comparably well.

4.5.2 Rolling Window Performance Ratios

This section is a dynamic analysis of smart beta portfolio performance using rolling window metrics. We compute 63-day rolling Sharpe and Sortino ratios, alongside two Information ratios, to analyze the evolving risk-adjusted returns and strategy effectiveness over time. These measures provide insights into how US and EU Smart Beta portfolios responded during periods of market stress, with particular attention to COVID-19 and the Russia-Ukraine war. Rolling metrics are especially useful for identifying shifts in performance linked to changing volatility regimes, investor sentiment, and market conditions.

The results in Figure 4.2 indicate that the beginning of each crisis led to a consistent decline in Sharpe ratios across all strategies and regions, suggesting that systemic shocks put broadly similar pressure on smart beta portfolios regardless of the underlying factor or geographic focus. While all strategies responded negatively, the differences in their performance were modest.

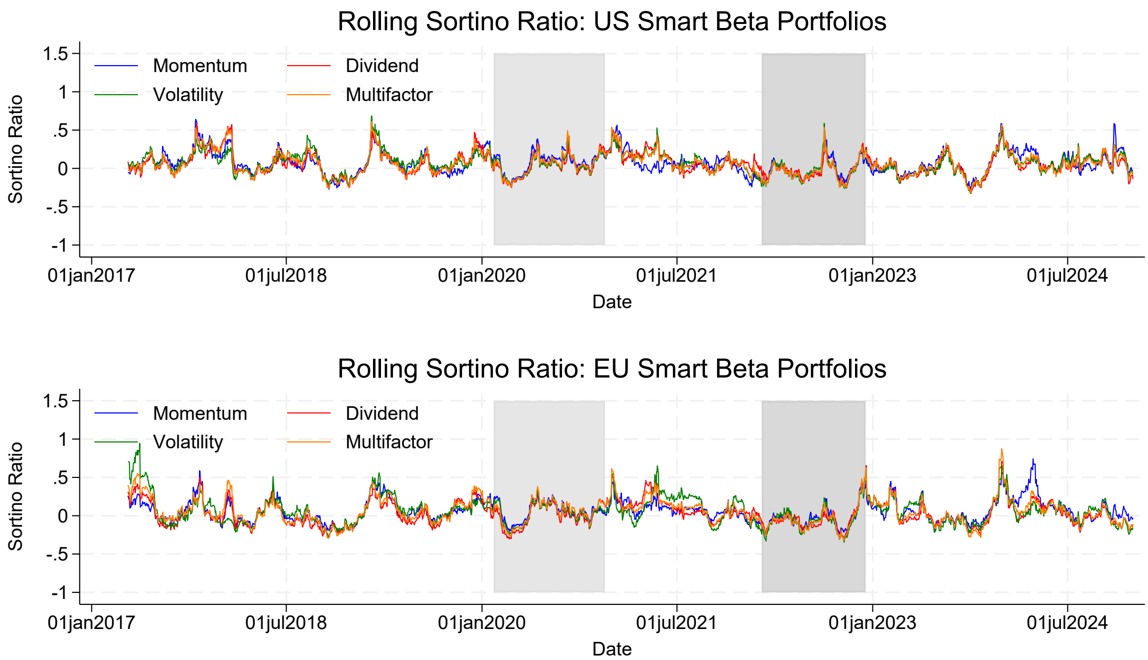
Fig. 4.2: Rolling Sharpe Ratio US vs. EU



Note: This figure compares the performance stability of US and EU Smart Beta portfolios using 63-day rolling Sharpe Ratios. Gray shaded areas indicate our major crisis periods, COVID-19 and Russia-Ukraine war.

In particular, Momentum strategies in both the US and EU demonstrated slightly better resilience during the initial COVID-19 downturn, although this outperformance was marginal. More pronounced distinctions emerged in the post-crisis recovery phases. Following the COVID-19 crash, the EU Volatility strategy experienced a notably strong and sustained rebound in Sharpe ratios, suggesting its ability to adapt effectively in volatile recovery conditions. Conversely, the US Momentum strategy underperformed during the recovery, despite its relative strength during the downturn. This may reflect a shift in market leadership, particularly the decline of technology-driven momentum that dominated earlier stages of the pandemic. Dividend and multifactor strategies maintained a more neutral trajectory during the recovery, neither outperforming nor lagging significantly. In summary, while all smart beta strategies exhibited broadly similar behavior during crisis periods, with only marginal differences in downside resilience, recovery phases provided more informative distinctions. Volatility strategies showed consistently strong performance in the recovery phase of COVID, particularly in Europe. Momentum strategies, while relatively stable during downturns, proved more vulnerable in shifting market environments, especially in the US.

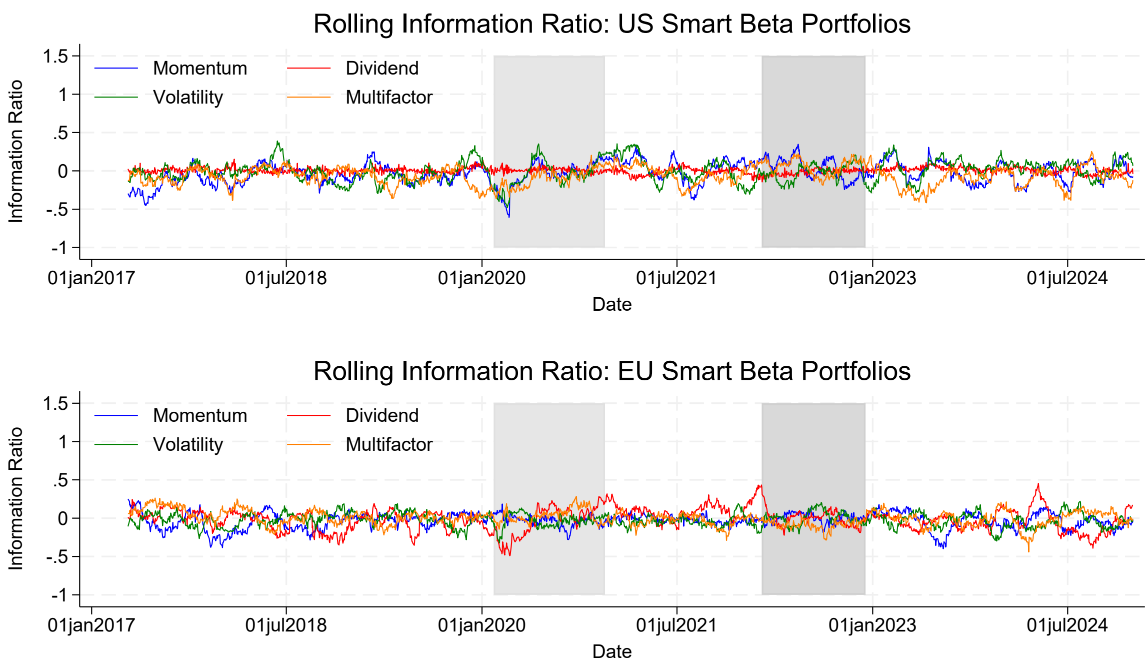
Fig. 4.3: Rolling Sortino Ratio US vs. EU



Note: This figure compares the performance stability of US and EU Smart Beta portfolios using 63-day rolling Sortino Ratios. Gray shaded areas indicate our major crisis periods, COVID-19 and Russia-Ukraine war.

Following the Sharpe ratio analysis, the Sortino ratio provides additional insight into the performance of smart beta strategies by isolating downside volatility. Unlike the Sharpe ratio, which considers total volatility, the Sortino ratio focuses on harmful volatility, thus offering a more targeted view of risk-adjusted return during adverse market conditions. This makes it particularly relevant for assessing behavior during crisis periods such as the COVID-19 pandemic and the Russia-Ukraine conflict. Visual inspection of the rolling 63-day Sortino ratios for both US and EU Smart Beta portfolios reveals broadly similar dynamics to those observed in the Sharpe ratios. Crises led to sharp declines in the Sortino ratio across all strategies and regions, confirming that downside risk surged across the board. However, Sortino ratios tend to show slightly lower troughs during crisis periods compared to Sharpe ratios, particularly in the EU, which reflects that downside volatility was more pronounced than total volatility alone would suggest. A notable feature of the Sortino ratio trends is the clearer separation between strategies during recovery periods, especially following the COVID-19 shock. In the US, Momentum exhibited a weak recovery, with Sortino ratios remaining subdued compared to the other strategies. In contrast, dividend, volatility, and multifactor portfolios all showed relatively stable and consistent improvements, reflecting a more balanced downside-risk-adjusted performance during the market rebound. In the EU, the most pronounced improvement was seen in the volatility strategy, which demonstrated a strong and sustained recovery in Sortino ratios, outperforming the other regional strategies. In the Russia-Ukraine crisis, Sortino

Fig. 4.4: Rolling Information Ratio with factor-specific Benchmark: US vs. EU

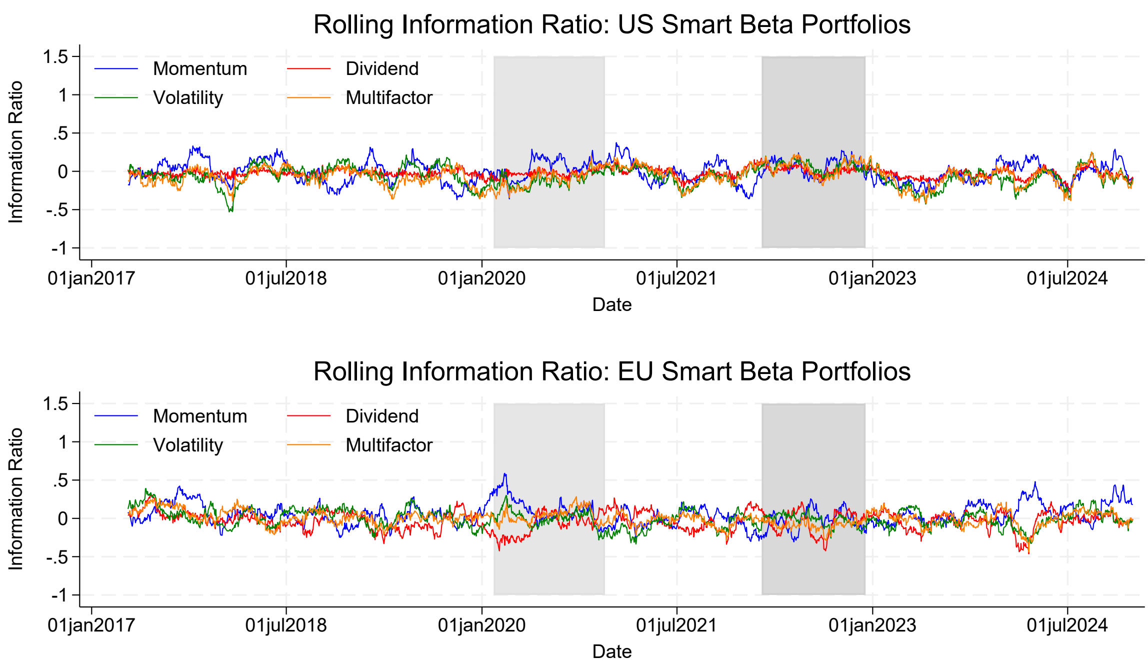


Note: This figure compares the performance stability of US and EU Smart Beta portfolios using 63-day rolling Information Ratios. The benchmark for the respective ratio is factor-specific and can be seen in Table 3.3. Gray shaded areas indicate our major crisis periods, COVID-19 and Russia-Ukraine war.

ratios fell across all strategies, though the impact was less severe than during the pandemic. Volatility strategies again stood out, but with a distinct regional pattern: in the mid-crisis phase, the US volatility strategy maintained relatively higher Sortino ratios. However, as the crisis progressed, the EU volatility strategy overtook its US counterpart, exhibiting stronger and more sustained Sortino performance during the recovery phase.

The Information Ratio is used to assess the performance of smart beta strategies relative to both their respective factor benchmarks and to broad market indices. Two specifications are considered: the IR relative to the respective factor benchmark, and the IR relative to the broad market, the S&P 500 for US portfolios and the EURO STOXX 600 for EU portfolios. These metrics capture the degree and consistency of active return, allowing for a closer look at relative positioning during crises and the following recovery phases. Starting with the factor-specific IRs, clear regional differences emerge. In the US, the dividend strategy maintains values consistently near zero throughout the entire sample, suggesting a near-perfect tracking of its benchmark with neither persistent outperformance nor underperformance.

Fig. 4.5: Rolling Information Ratio with market Benchmark: US vs. EU



Note: This figure compares the performance stability of US and EU Smart Beta portfolios using 63-day rolling Information Ratios. The S&P 500 and the EURO STOXX 600 are the benchmarks for US and EU portfolios. Gray shaded areas indicate our major crisis periods, COVID-19 and Russia-Ukraine war.

In contrast, EU Dividend strategies show significant fluctuations, particularly during the early stages of the COVID-19 pandemic and again immediately before the outbreak of the Russia-Ukraine war. This reflects greater instability in relative performance within the European dividend assets. In the US, all strategies except dividend exhibit negative IRs, often close to -0.5, indicating ongoing underperformance relative to their factor benchmarks.

A contrast appears within the US itself: During the Russia-Ukraine war period, momentum and multifactor show an inverse outperformance pattern compared to volatility, implying opposing tracking behaviors among these strategies over time.

Turning to the market-relative IRs, further regional differences become evident. At the beginning of the COVID-19 crisis, EU momentum, volatility, and multifactor strategies all exhibit strong outperformance relative to the EURO STOXX 600, with IR values rising significantly. However, this outperformance diminishes as the pandemic progresses, with values returning to levels near zero. Interestingly, the US momentum strategy shows the opposite behavior: it underperforms the S&P 500 sharply at the onset of COVID-19, before stabilizing later in the pandemic. This suggests differing sector exposures and crisis responses between the US and EU momentum portfolios. During the Russia-Ukraine war, EU market-relative IRs fluctuate around zero in wave-like patterns, reflecting alternating periods of mild outperformance and underperformance. In contrast, US IR values remain more steady and closer to the zero line, indicating more consistent but modest relative performance across the war period.

Together, these patterns highlight significant regional and strategic differences in the behavior of smart beta strategies when measured against both factor-specific and broad market benchmarks. The US dividend strategys tight tracking, the EU dividend strategys volatility, and the opposing crisis responses of momentum strategies across regions all underscore the complexity of relative performance dynamics during periods of market stress and recovery.

5 Discussion

H1: *The momentum factor (WML) exhibits a dominant and increasing influence on Smart Beta ETF returns during periods of financial crisis and elevated market uncertainty.*

The empirical findings offer partial support for Hypothesis 1. Throughout both the COVID-19 pandemic and the Russia-Ukraine war, the momentum factor remained a statistically significant and economically relevant driver of returns, particularly for ETFs explicitly designed to capture momentum. Momentum ETFs in both the US and Europe displayed strong, positive, and consistent WML loadings throughout both crisis periods, reaffirming their alignment with trend-following strategies. More interestingly, the results indicate that momentum exposure not only persisted, but often increased during crises, especially during the Russia-Ukraine war. The Momentum Smart Beta ETFs from the US and Europe both strengthened their WML loadings in that period, suggesting that trend-based strategies continued to function effectively, even under geopolitical stress. This trend was somewhat muted during COVID-19, particularly in Europe, where a modest decrease in WML exposure was observed. However, even outside momentum ETFs, some strategies, such as European Dividend Smart Beta ETFs, showed increased WML sensitivity, pointing to subtle, crisis-driven shifts toward short-term performance chasing. These crisis-driven adjustments in WML exposure outside of dedicated momentum strategies can be interpreted through the lens of time-varying risk premia and behavioral finance. The theory of conditional factor pricing by (Ferson & Schadt, 1996) provides a framework for understanding these shifts, as it proposes that factor exposures are not fixed but vary with changing economic and market conditions. In this context, the temporary increase in WML exposure among non-momentum ETFs during crises may indicate a passive response to market volatility or unintentional exposure through correlated characteristics. This behavior is consistent with (Barroso & Santa-Clara, 2015) finding that momentum can persist under volatility when actively risk-managed. In their study, they propose a volatility-managed momentum strategy that adjusts exposure based on recent volatility. This approach significantly reduces drawdowns and improves risk-adjusted returns. It is especially relevant during crises when unmanaged momentum strategies tend to suffer from sharp reversals and amplified volatility. Most Smart Beta ETFs do not apply such dynamic adjustments. Their rules-based structures limit the ability to reduce risk in real time. Therefore, while the theoretical momentum premium may remain intact during crises, the realized benefit in standard Smart Beta ETFs is limited. Similarly, the momentum crash identified by (Daniel & Moskowitz, 2016) helps explain the drop in WML exposure in European Momentum ETFs during COVID-19. Their research shows that momentum strategies can suffer large and sudden losses during sharp market reversals. These occur when investors rotate out of past winners into previously underperforming stocks. This matches the conditions at the start of the COVID-19 crisis. After a steep decline, markets rebounded abruptly, reversing short-term return patterns. In this environment, recent winners underperformed, disrupting the trend-following mechanism of momentum. Our findings reflect this: the decline in WML exposure in European Momentum ETFs was likely a rational response to worsening conditions for momentum-based investing. These ETFs may have temporarily shifted their holdings to avoid further losses or to align better with changing market sentiment. Although WML remained significant for Momentum ETFs in both crises, its influence was much less pronounced in other strategies. Before both crises, WML exposure was largely isolated to Momentum ETFs. During the crises, other ETF categories showed small but positive shifts in momentum exposure. This indicates a broader, yet still secondary, uptake of momentum traits under stress. While momentum tendencies may rise during market turbulence, WML does not become a dominant return driver in ETFs not specifically targeting it. Therefore, the results support a more restrained view of momentums role in broad Smart Beta behavior. For investors, these dynamics highlight the need to understand that Smart Beta ETFs are not immune to shifts in factor sensitivity during market crises. While often marketed as passive or rules-based, these products can behave differently when stress hits the system. Relying on historical labels or pre-crisis behavior may lead to misaligned expectations. It is essential to monitor how factors like momentum behave in real time. For institutional asset allocators, this reinforces the importance of building regime-awareness into portfolio strategies. Regime-awareness refers to the practice of adjusting exposure based on distinct market conditions such as calm periods, high volatility, or recovery phases. Momentum is particularly vulnerable to disruption during regime shifts. If ignored, these shifts can result in unexpected portfolio behavior. This knowledge can be used to improve risk control, recalibrate factor weights during stress, and ensure that actual ETF behavior aligns more closely with investor goals.

H2: *European Smart Beta ETFs exhibit significantly more pronounced and volatile shifts in factor exposures compared to US-based ETFs during periods of market stress.*

The findings strongly support Hypothesis 2. EU Smart Beta ETFs demonstrated greater variability and less consistency in factor exposures than US ETFs, particularly during periods of systemic market stress. In contrast, US ETFs exhibited more stable and persistent loadings, especially for the MRP and the SMB factor, consistent with structurally embedded exposure patterns. During the COVID-19 crisis, European ETFs showed significant increases in MRP and SMB loadings. This suggests a reactive pivot toward broader market and small-cap exposures, possibly driven by either rebalancing or attempts to capture recovery gains. These shifts were especially pronounced in traditionally conservative categories such as volatility and dividend ETFs, implying a tactical response to crisis dynamics rather than passive adherence to pre-crisis strategies. However, during the Russia-Ukraine war, the pattern reversed: Many European ETFs decreased exposure to MRP and SMB, reflecting a defensive repositioning possibly in response to increased geopolitical risk. These contrasting reactions are not random but align with key findings in the literature. (Rao et al., 2018) examine international Smart Beta portfolios and show that factor tilts are not static. They adjust based on macroeconomic regimes and regional investment behavior. This supports our observation that European ETFs changed exposures more dramatically in response to crisis stress. However, other studies present a more stable picture of European ETF exposures. (Dirkx, 2019) conducted a holdings- and regression-based study over a ten-year period and found that many European ETFs maintained significant and persistent exposures to core factors such as market, size, and value. This suggests that some Smart Beta products in Europe offer more consistency than our crisis-period findings imply. Similarly, (Bowes & Ausloos, 2021) examined 145 EU-domiciled Smart Beta ETFs over twelve years. They found that equal-weighted and momentum-based ETFs achieved better risk-adjusted returns while also maintaining consistent factor exposures. These results contrast with our observations of high variability, particularly during crisis phases, and indicate that longer-term factor stability may still be achievable within the European Smart Beta space. (Lettau & Ludvigson, 2001) develop a conditional consumption capital asset pricing model (CCAPM) which shows that expected returns and factor sensitivities vary with economic conditions. This matches our findings, particularly in the shift from risk-seeking to risk-averse exposure profiles in European ETFs across the two crises. Furthermore, (D. Blitz et al., 2013) provide evidence that Smart Beta strategies reflect behavioral biases and exhibit time-varying risk characteristics, depending on investor sentiment and market phase. This helps explain the more reactive nature of European ETFs. (Fama & French, 2015) find that regional characteristics shape factor premiums, particularly size and value, which supports the observed difference in factor behavior between US and European ETFs. Their findings suggest that structural constraints and investor preferences can lead to more persistent size premia in US markets. In addition, (Goldstein et al., 2021) show that geopolitical shocks and intangible capital shifts reduce the explanatory power of traditional value factors, particularly in European contexts. This aligns with our findings that value factor loadings in European ETFs were more unstable during crises. These studies help explain why European ETFs may display more pronounced changes in factor exposure during systemic events. In practice, this knowledge highlights critical considerations for both investors and policymakers. For investors, the results indicate that Smart Beta ETFs are not uniformly reliable across regions in maintaining intended factor exposures. Particularly in Europe, these products appear more susceptible to design drift or crisis-induced repositioning. This greater sensitivity to market conditions implies that European ETFs may either capitalize on regime-specific opportunities or amplify volatility if exposures shift unpredictably. As such, investors must not rely solely on fund labels or historical loadings but should actively monitor factor exposures, especially in multi-region portfolios and during market stress. The greater variability observed in European ETFs suggests they may reflect more opportunistic or sentiment-driven responses to macroeconomic and geopolitical events. For investors, this creates both potential for tactical gains and risk of unexpected behavior. In contrast, the relative stability of US ETFs may make them more suitable for long-term strategic allocations where consistent exposure is prioritized. For institutional investors, portfolio construction models should account for the likelihood of regional behavioral asymmetries in response to macro shocks. Regime-aware allocations that recognize the conditional nature of factor exposure can lead to more resilient risk-adjusted outcomes. This means incorporating market conditions and ETF design characteristics into factor models and adjusting weights accordingly. For ETF issuers and regulators, the evidence supports calls for enhanced transparency regarding the conditions under which factor loadings may deviate from expectations. Without this, investors face the risk of unintended exposures at exactly the time they seek stability. Overall, the findings reinforce the argument that Smart Beta strategies are not immune to market regime changes and must be evaluated dynamically. Regional differences in ETF responsiveness during crisis events demand a more nuanced approach to using factor-based products in global asset allocation strategies. This includes not only selecting factors but also understanding how these exposures may change in different regions under stress.

H3: *Smart Beta ETFs do consistently outperform either their respective factor benchmarks or broad market indices on a risk-adjusted basis, particularly during and following periods of financial crisis.*

The empirical findings in this study do not offer clear support for Hypothesis 3. Annualized and rolling performance measures produce mixed results. Periods of temporary outperformance are frequently followed by longer episodes of underperformance or neutral behavior, particularly during and after financial crises. Across the full sample, Smart Beta ETFs outperform their respective factor benchmarks in only 33.33% of Sharpe ratio comparisons. This suggests that these products do not demonstrate a consistent advantage in terms of risk-adjusted performance. Information Ratios across most strategies are also close to or below zero, indicating weak tracking efficiency relative to either benchmarks or the broad market. (Mateus et al., 2020) examine Smart Beta ETFs in the United States and report that about 40 percent outperform their traditional counterparts after accounting for costs. They also find statistically significant performance persistence in the majority of peer groups, with consistent winners observed in 7 out of 9 categories. These results suggest that persistence may exist within certain segments of the US market. However, their sample predates recent crisis periods such as the COVID-19 pandemic and the Russia-Ukraine war. In contrast, the present study finds no such persistence, especially within European Smart Beta ETFs. This difference may reflect variations in geographic focus, product design, or the economic conditions covered in each study. Our results also indicate that Smart Beta ETFs rarely sustain outperformance, particularly during volatile or transitional market conditions. One explanation may be the nature of Smart Beta ETFs themselves. Unlike actively managed mutual funds, these ETFs follow strict rules-based methodologies, which limit their ability to adjust exposures in real time. Rolling performance data during the COVID-19 pandemic and the Russia-Ukraine conflict reinforce these findings. Sharpe and Sortino ratios dropped sharply across all ETF strategies and regions when each crisis began. Momentum-based strategies in both the US and Europe showed some initial resilience but did not maintain their advantage. Volatility-focused strategies in Europe performed better during certain recovery phases, although these gains were not consistent over the full sample period. Factor-relative Information ratios remained low throughout. For example, the US dividend strategy closely tracked its benchmark without generating excess returns, while the EU dividend strategy displayed erratic and unstable performance, particularly around the COVID-19 shock and the early stages of the Russia-Ukraine conflict. (D. Blitz & Hanauer, 2021) critiques traditional value investing strategies, particularly those based on the HML factor, arguing that these approaches have become ineffective due to outdated metrics and crowding effects. He proposes alternative metrics, such as EBITDA over enterprise value and net payout yield, alongside portfolio constraints like industry neutrality. While focused on value, these observations highlight a broader challenge. Our results indicate that many Smart Beta ETFs suffer from similar structural limitations. Their rigid methodologies prevent them from responding to changing market conditions, which in turn limits their ability to deliver consistent performance. (B. Li & Rossi, 2021) investigate the impact of factor misalignment and find that performance deteriorates when a strategy's targeted exposures do not match prevailing market conditions. Their work on dynamic factor investing shows that even well-constructed strategies underperform when they are not synchronized with current return drivers. This aligns closely with our findings. Smart Beta ETFs often fail to adapt during periods of disruption, which may explain their weak performance during and after crises. Fixed rebalancing schedules and inflexible design structures appear to prevent timely adjustments in factor exposures. (Huang et al., 2024) offer another explanation for Smart Beta underperformance. They examine index behavior before and after ETF launch and find that strong backtested performance typically fades once a product becomes publicly traded. This suggests that the outperformance may result from overfitting historical data rather than capturing genuine factor premiums. This observation supports our finding that some Smart Beta strategies, including momentum and volatility, appear resilient at the onset of a crisis but quickly lose that edge. The evidence suggests that overly optimized index design undermines performance in real market conditions. (Foglia et al., 2021) provide evidence that Smart Beta strategies which incorporate macroeconomic signals into their allocation decisions tend to perform better during economic stress. Their analysis of multifactor portfolios during the COVID-19 period highlights the benefits of flexible asset allocation in response to changing macro indicators. The ETFs in our study, by contrast, rely on static, rules-based structures that do not incorporate macro signals. This lack of adaptability may be a key reason why they fail to realize the theoretical advantages often attributed to factor investing. Finally, (Ding et al., 2022) evaluates Smart Beta ETFs in the US from 2009 to 2019 and finds that they do not generate consistent, risk-adjusted outperformance. His results extend the literature by showing that these products underperform across multiple market regimes, including recovery phases. These conclusions are consistent with our own findings, which show weak and unstable performance across different regions and crisis periods.

In summary, while Smart Beta strategies appear conceptually attractive and often show promise in historical simulations, their actual implementation in ETF formats has not produced sustained, risk-adjusted outperformance. The static nature of these products, combined with design rigidities and timing misalignments, appears to limit their effectiveness, particularly during periods of economic disruption or market transition.

5.1 Limitations and Future Research

While this study provides valuable information on the behavior of ETF factor strategies during different crisis periods, several limitations should be recognized. These limitations do not undermine the core findings, but rather highlight areas where future research could build on and refine the results. In recognition of these limitations, this section also outlines potential avenues for further investigation that could improve the robustness, generalizability, and practical applicability of the studys conclusions.

Limitations:

Although the main findings are robust under the Carhart model, additional analysis using the six-factor specification revealed multicollinearity probabilities between HML and

CMA. However, these checks confirmed the dominant role of MRP and WML. Several other limitations must be acknowledged. First, the one-month US T-bill rate is used as the risk-free rate for both the US and Europe. Although this choice ensures internal consistency across excess returns and MRP construction, it may not optimally reflect the true risk-free rate in European markets. Second, the sample of Smart Beta ETFs, particularly in Europe, is relatively small. Some strategy categories, such as EU Momentum, consist of as few as four ETFs, and many funds have short lifespans (e.g., 14 months), which limits the length and reliability of panel observations. Third, although fixed effects (FE) were chosen for their capacity to isolate within-ETF variation, the Hausman test favored random effects (RE), indicating that FE may not be the statistically optimal model. Fourth, the high correlation between HML and CMA in the six-factor model introduces multicollinearity that complicates interpretation, although this issue is less critical given the robustness role of the extended model. Fifth, the use of clustered standard errors (vce cluster) was essential to account for autocorrelation and heteroskedasticity across ETFs, but also reflects the non-independence of returns. Lastly, while Smart Beta ETFs were selected using transparent criteria, there is no universally fixed standard for defining these strategies, which introduces a degree of subjectivity and potential selection bias. These constraints may limit the generalizability of results, but do not detract from the core insights derived from the Carhart specification. When it comes to the performance analysis of the Smart Beta Factor portfolios, there are also some limitations to acknowledge. The portfolios are constructed by equally weighting the respective ETFs in the factor category. This also means that ETFs with low assets under management or limited time in the market have the same influence on the return as well-established and stable funds.

Future Research:

This gap highlights several promising directions for future academic research. First, based on the limitations of this study, empirical work could estimate the time-varying factor loadings for Smart Beta ETFs during the 2022-2023 period, using techniques such as rolling regressions or Kalman filter models to better capture evolving exposure patterns beyond static models. Second, more research is needed on the impact of geopolitical risk, considered separately from broader economic uncertainty, on both factor premia and capital allocation in Smart Beta products. Third, as ETF trading volumes and return volatility increased during the initial phases of the Russia-Ukraine War, future studies should assess whether Smart Beta ETFs amplified or mitigated systemic risk through their liquidity, tracking error, and investor flow dynamics. Finally, analysis of firm-level ETF holdings could yield insights into microlevel factor alignment, while comparative studies involving active funds or other geographic regions would improve our understanding of

Smart Beta resilience and adaptability during both global and localized crises. In regard to the performance analysis of Smart Beta ETFs, future research could increase the sample size, include other regions, or more in-depth ratios. This could be done by combining a rolling beta regression for exposure analysis with a rolling performance ratio, such as the Treynor ratio. By doing so, one could get a more nuanced picture of time-varying shifts of Smart Beta ETFs.

6 Conclusion

This thesis investigates the behavior of Smart Beta ETFs during periods of market stress, focusing on the evolution of factor exposures and performance across US and European markets. Drawing on a panel of over 200 Smart Beta ETFs categorized into momentum, dividend, low volatility, and multifactor strategies, the study examines their sensitivities to systematic risk factors using extended asset pricing models. To capture shifts in factor loadings during crisis periods, panel regressions incorporating crisis-specific interaction terms are employed for two key events: the COVID-19 pandemic and the Russia-Ukraine war. In addition, a detailed performance assessment is carried out using rolling Sharpe, Sortino, and Information Ratios to evaluate the risk-adjusted performance of Smart Beta ETFs under stress conditions.

The analysis reveals that momentum emerged as a more influential return driver during periods of market turmoil, particularly within ETFs explicitly designed to capture momentum strategies. This effect was especially noticeable during the Russia-Ukraine war, where momentum exposures intensified across both US and European markets. However, this influence was not consistent across all ETF categories or regions. For many strategies not specifically focused on momentum, the role of this factor remained secondary, and in some cases, such as European momentum ETFs during the COVID-19 pandemic, exposure to momentum even declined, reflecting the sensitivity of these strategies to rapid market reversals.

The study also finds that European Smart Beta ETFs tend to exhibit more pronounced and volatile shifts in factor exposures compared to their US counterparts. This greater variability suggests a higher degree of reactivity to market stress in European ETFs, potentially driven by differences in fund construction, investor behavior, or regional market dynamics. In contrast, US-based ETFs demonstrated more stable and persistent exposures throughout both crisis periods, indicating a relatively more systematic factor alignment.

Lastly, this thesis has no strong evidence supporting an outperformance of Smart Beta ETFs. The Smart Beta ETFs outperformed their factor-specific benchmarks in only 33.33% of Sharpe ratio comparisons, with Information ratios often near or below zero. Results were especially weak during both crisis periods, and no consistent pattern of risk-adjusted outperformance was observed across regions or strategies. The crisis behavior varied across the categories, showing momentum as the strongest performer during the onset of both crises, followed by a decline in the recovery periods. Low volatility had an inverse reaction by underperforming during the crisis and a strong performance in the recovery phase.

This thesis contributes to the literature by providing a cross-regional, multi-crisis analysis of Smart Beta ETFs, offering practical insights into their robustness and informing asset allocation decisions under financial stress. The findings underscore the importance of understanding dynamic factor exposures in evaluating the reliability of smart beta products as a hybrid investment class.

Nevertheless, his study is subject to several limitations, including a limited European ETF sample, potential multicollinearity in the six-factor model, and the use of a US risk-free rate for both regions. Model selection challenges and possible selection bias in ETF classification also constrain generalizability. Future research could explore time-varying factor exposures, the role of geopolitical risk, and the systemic impact of Smart Beta ETFs using dynamic models and broader, cross-regional datasets.

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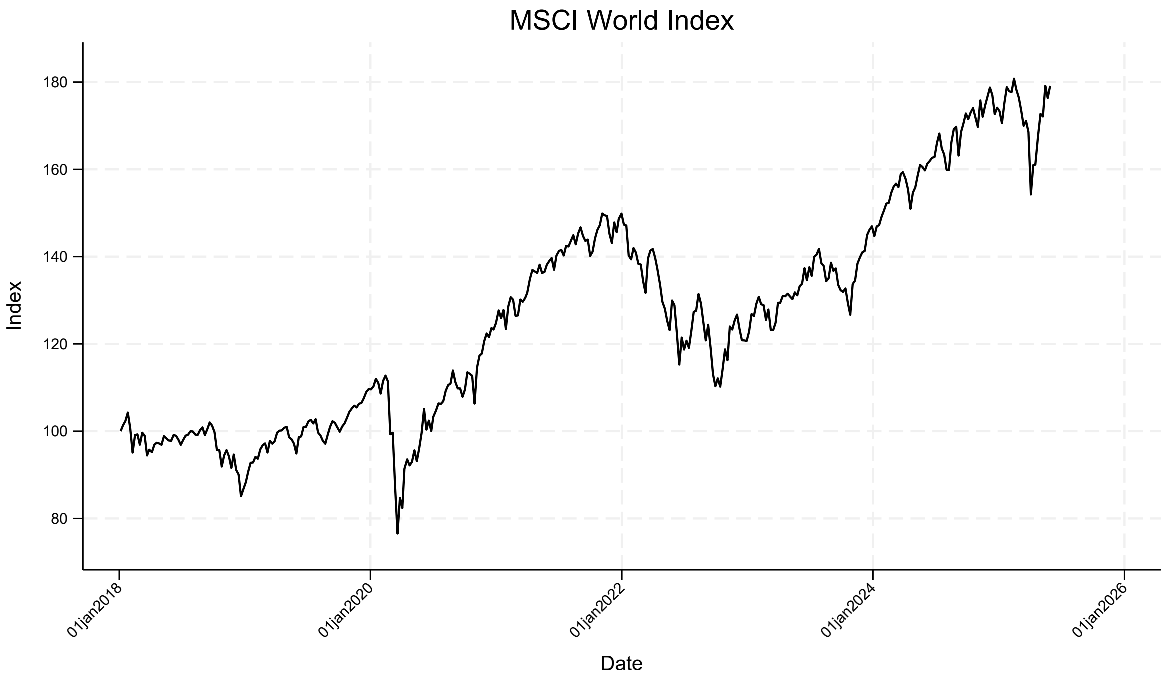
A Appendix

Fig. A.1: MSCI World Index from 2018 to 2025



Note: This figure shows the MSCI World Index from 2018 to 2025. The index is normalized to 100 as of January 1, 2018. Source: FactSet

Table A.1: Variable Definitions, Factor Models, and Crisis Periods

Variable	**Symbol**	**Definition**	**Used In**
Excess Return	$R_{i,t}^{\text{excess}}$	ETF return minus the risk-free rate	All regressions (dependent variable)
Market Risk Premium	MRP	Market return minus the risk-free rate	CAPM, FF3, Carhart, FF5, 6-Factor
Size	SMB	Return premium of small-cap stocks over large-cap stocks	FF3, Carhart, FF5, 6-Factor
Value	HML	Return of high B/M stocks minus low B/M stocks	FF3, Carhart, FF5, 6-Factor
Momentum	WML	Return of past winners minus losers (12-month lookback)	Carhart, 6-Factor
Profitability	RMW	Return of firms with robust vs. weak profitability	FF5, 6-Factor
Investment	CMA	Return of conservative vs. aggressive investing firms	FF5, 6-Factor
COVID-19 Dummy	D^{COVID}	Equals 1 during Feb-Dec 2020, 0 otherwise	Interacted with all factors in panel regressions
War Dummy	D^{WAR}	Equals 1 during Feb-Dec 2022, 0 otherwise	Interacted with all factors in panel regressions
Factor Models			
CAPM	1-Factor	$R^{\text{excess}} = \alpha + \beta_M \cdot \text{MRP} + \varepsilon$	Benchmark model using only market risk
Fama-French	3-Factor	Adds SMB and HML to CAPM	Captures size and value premia
Carhart	4-Factor	Adds WML (momentum) to FF3	Includes momentum premium
Fama-French	5-Factor	Adds RMW and CMA to FF3	Adds profitability and investment factors
Extended	6-Factor	Combines FF5 and Carhart (adds WML to FF5)	Most comprehensive model used

Note: This table provides definitions and roles of all key variables used in the empirical analysis, including factor variables, crisis period dummies, and their application across different asset pricing models. Factor models are listed separately, with the corresponding number of factors indicated for clarity. Interaction terms with crisis dummies are used to assess time-varying factor sensitivities during the COVID-19 pandemic (Feb-Dec 2020) and the Russia-Ukraine war (Feb-Dec 2022).

Table A.2: List of all Smart Beta ETFs and Benchmarks

ID	Ticker	Smart Beta ETF	Size	Category	Region
1	QMOM	Alpha Architect U.S. Quantitative Momentum ETF	2284	Momentum	US
2	PYZ	Invesco Dorsey Wright Basic Materials Momentum ETF	4584	Momentum	US
3	PEZ	Invesco Dorsey Wright Consumer Cyclicals Momentum ETF	4584	Momentum	US
4	PSL	Invesco Dorsey Wright Consumer Staples Momentum ETF	4584	Momentum	US
5	PXI	Invesco Dorsey Wright Energy Momentum ETF	4584	Momentum	US
6	PFI	Invesco Dorsey Wright Financial Momentum ETF	4584	Momentum	US
7	PTH	Invesco Dorsey Wright Healthcare Momentum ETF	4584	Momentum	US
8	PRN	Invesco Dorsey Wright Industrials Momentum ETF	4584	Momentum	US
9	PDP	Invesco Dorsey Wright Momentum ETF	4490	Momentum	US
10	DWAS	Invesco Dorsey Wright SmallCap Momentum ETF	3132	Momentum	US
11	PTF	Invesco Dorsey Wright Technology Momentum ETF	4584	Momentum	US
12	PUI	Invesco Dorsey Wright Utilities Momentum ETF	4826	Momentum	US
13	SPMO	Invesco S&P 500 Momentum ETF	2321	Momentum	US
14	MTUM	iShares MSCI USA Momentum Factor ETF	2946	Momentum	US
15	JMOM	JPMorgan U.S. Momentum Factor ETF	1795	Momentum	US
16	ONEO	SPDR Russell 1000 Momentum Focus ETF	2283	Momentum	US
17	MMTM	SPDR S&P 1500 Momentum Tilt ETF	3063	Momentum	US
18	VFMO	Vanguard U.S. Momentum Factor ETF	1729	Momentum	US

ID	Ticker	Smart Beta ETF	Size	Category	Region
19	ULVM	VictoryShares US Value Momentum ETF	1805	Momentum	US
20	BF2JVZ	AMUNDI MSCI EUROPE MOMENTUM FACTOR UCITS ETF	2165	Momentum	EU
21	BG13YJ	iShares Edge MSCI Europe Momentum Factor UCITS ETF	1721	Momentum	EU
22	BVJDPF	iShares Edge MSCI Europe Momentum Factor UCITS ETF	2502	Momentum	EU
23	BYM3ZS7	BNP Paribas Easy SICAV - ESG Momentum Europe UCITS ETF Distribution	1987	Momentum	EU
24	SDOG	ALPS Sector Dividend Dogs ETF	3145	Dividend	US
25	CGUS	Capital Group Core Equity ETF	716	Dividend	US
26	FDVV	Fidelity High Dividend ETF	2086	Dividend	US
27	FDL	First Trust Morningstar Dividend Leaders Index Fund	4731	Dividend	US
28	TDIV	First Trust NASDAQ Technology Dividend Index Fund	3114	Dividend	US
29	RDVY	First Trust Rising Dividend Achievers ETF	2764	Dividend	US
30	KNGZ	First Trust S&P 500 Diversified Dividend Aristocrats ETF	1894	Dividend	US
31	SDVY	First Trust SMID Cap Rising Dividend Achievers ETF	1800	Dividend	US
32	FVD	First Trust Value Line Dividend Index Fund	5032	Dividend	US
33	QDIV	Global X S&P 500 Quality Dividend ETF	1625	Dividend	US
34	BDVG	iMGP Berkshire Dividend Growth ETF	378	Dividend	US
35	PFM	Invesco Dividend Achievers ETF	4855	Dividend	US
36	PEY	Invesco High Yield Equity Dividend Achievers ETF	5032	Dividend	US
37	KBWD	Invesco KBW High Dividend Yield Financial ETF	3542	Dividend	US

ID	Ticker	Smart Beta ETF	Size	Category	Region
38	RDIV	Invesco S&P Ultra Dividend Revenue ETF	2831	Dividend	US
39	DIVB	iShares Core Dividend ETF	1795	Dividend	US
40	DGRO	iShares Core Dividend Growth ETF	2656	Dividend	US
41	HDV	iShares Core High Dividend ETF	3460	Dividend	US
42	DVY	iShares Select Dividend ETF	5032	Dividend	US
43	JDIV	JPMorgan Dividend Leaders ETF	66	Dividend	US
44	FDIV	MarketDesk Focused U.S. Dividend ETF	322	Dividend	US
45	PY	Principal Value ETF	2209	Dividend	US
46	SMDV	ProShares Russell 2000 Dividend Growers ETF	2492	Dividend	US
47	NOBL	ProShares S&P 500 Dividend Aristocrats ETF	2824	Dividend	US
48	REGL	ProShares S&P MidCap 400 Dividend Aristocrats ETF	2492	Dividend	US
49	FNDX	Schwab Fundamental U.S. Large Company ETF	2863	Dividend	US
50	SCHD	Schwab US Dividend Equity ETF	3319	Dividend	US
51	SPYD	SPDR Portfolio S&P 500 High Dividend ETF	2312	Dividend	US
52	SDY	SPDR S&P Dividend ETF	4812	Dividend	US
53	DURA	VanEck Durable High Dividend ETF	1550	Dividend	US
54	VIG	Vanguard Dividend Appreciation ETF	4701	Dividend	US
55	VYM	Vanguard High Dividend Yield Index ETF	4559	Dividend	US
56	WBIY	WBI Power Factor High Dividend ETF	2018	Dividend	US
57	DEW	WisdomTree Global High Dividend Fund	4666	Dividend	US
58	DLN	WisdomTree U.S. LargeCap Dividend Fund	4666	Dividend	US

ID	Ticker	Smart Beta ETF	Size	Category	Region
59	DON	WisdomTree U.S. MidCap Dividend Fund	4666	Dividend	US
60	DES	WisdomTree U.S. SmallCap Dividend Fund	4666	Dividend	US
61	DTD	WisdomTree U.S. Total Dividend Fund	4666	Dividend	US
62	DHS	WisdomTree U.S. High Dividend Fund	4666	Dividend	US
63	BMCLCG	Amundi DivDAX UCITS ETF Distribution	3427	Dividend	EU
64	B3VC5H	Amundi ETF FTSE UK Dividend Plus UCITS ETF FCP	1241	Dividend	EU
65	BMCLCN	Amundi Euro Stoxx Select Dividend 30 -UCITS ETF- Distribution	4106	Dividend	EU
66	BGKF96	Amundi STOXX Europe Select Dividend 30 - UCITS ETF Dist	4566	Dividend	EU
67	BF13XZ	BNP PARIBAS EASY SICAV - Dividend Europe -UCITS ETF-Capitalisation	1827	Dividend	EU
68	B3XV42	Deka DAXplus Maximum Dividend UCITS ETF	3955	Dividend	EU
69	BYNFCD	Deka EURO iSTOXX ex Fin Dividend+ UCITS ETF	2329	Dividend	EU
70	B3BDTC	Deka EURO STOXX Select Dividend 30 UCITS ETF	4153	Dividend	EU
71	FDD	First Trust Stoxx European Select Dividend Index Fund	4363	Dividend	US
72	B0791H	iShares DivDAX UCITS ETF (DE)	4964	Dividend	EU
73	B08TZF	iShares Euro Stoxx Select Dividend 30 UCITS ETF (DE)	4942	Dividend	EU
74	BMFV6J	iShares EURO STOXX Select Dividend 30 UCITS ETF (DE) Accumulating Shares	770	Dividend	EU

ID	Ticker	Smart Beta ETF	Size	Category	Region
75	B08V0F	iShares STOXX Europe Select Dividend 30 UCITS ETF (DE)	4942	Dividend	EU
76	BKM4H5	iShares Swiss Dividend ETF (CH)	2688	Dividend	EU
77	B0M630	iShares UK Dividend UCITS ETF GBP	4818	Dividend	EU
78	BGWL8P	KSM ETF (4A) EURO STOXX Dividend 30 Currency Hedged Units	1339	Dividend	EU
79	BHLYTC	KSM S&P TSX 60 (PR) (4DA) ETF	1288	Dividend	EU
80	BN7Q2G	Lyxor PEA EURO STOXX 50 Dividends UCITS ETF -C-EUR	498	Dividend	EU
81	B3M10Q	Lyxor UCITS ETF EUROSTOXX50 Dividends	1496	Dividend	EU
82	B4L306	Lyxor WIG20 UCITS ETF	3592	Dividend	EU
83	BZBXPW	MIRAE ASSET TIGER EURO STOXX DIVIDEND 30 ETF	2138	Dividend	EU
84	BMDHK9	Amundi S&P Eurozone Dividend Aristocrat Screened C-EUR- Capitalisation	833	Dividend	EU
85	BF8H5S	Multi Units Luxembourg SICAV - Amundi S&P Eurozone Dividend Aristocrat Screened -Dist- Distribution	2834	Dividend	EU
86	EUDV	ProShares MSCI Europe Dividend Growers ETF	2342	Dividend	EU
87	BHLYV0	Psagot ETF 4D STOXX Nordic Dividend 20 EUR	1288	Dividend	EU
88	BYZW35	Source FTSE RAFI UK Equity Income Physical UCITS ETF	336	Dividend	EU
89	BYTH5T	SPDR S&P Euro Dividend Aristocrats Screened UCITS ETF	898	Dividend	EU
90	B7KHKP	SPDR S&P Euro Dividend Aristocrats UCITS ETF	3230	Dividend	EU
91	B7L0SK	SPDR S&P UK Dividend Aristocrats UCITS ETF	3230	Dividend	EU

ID	Ticker	Smart Beta ETF	Size	Category	Region
92	BGWL9X	TACHLIT INDICES MUTUAL FUND MANAGEMENT LTD Units	1339	Dividend	EU
93	BQZJBZ	WisdomTree Europe Equity Income UCITS ETF	2562	Dividend	EU
94	BYQ7JD	WisdomTree Europe Equity Income UCITS ETF Acc	2048	Dividend	EU
95	BYYN9S	WisdomTree Europe Equity UCITS ETF CHF Hedged Acc	2242	Dividend	EU
96	BYY88S	WisdomTree Europe Equity UCITS ETF EUR Acc	2214	Dividend	EU
97	BYYN7Y	WisdomTree Europe Equity UCITS ETF GBP Hedged	2303	Dividend	EU
98	BWT3J9	WisdomTree Europe Equity UCITS ETF USD Hedged	2419	Dividend	EU
99	BYYN82	WisdomTree Europe Equity UCITS ETF USD Hedged Acc	2048	Dividend	EU
100	EUSC	WisdomTree European Opportunities Fund Units -P-	2474	Dividend	EU
101	DFE	WisdomTree Europe SmallCap Dividend Fund	4666	Dividend	US
102	BYPGTS	WisdomTree UK Equity Income UCITS ETF	2276	Dividend	EU
103	B1WJZ3	Xtrackers FTSE 100 Income UCITS ETF	4359	Dividend	EU
104	SMLF	iShares U.S. SmallCap Equity Factor ETF	2434	Multifactor	US
105	FDMO	Fidelity Momentum Factor ETF	2086	Multifactor	US
106	DVOL	First Trust Dorsey Wright Momentum & Low Volatility ETF	1589	Multifactor	US
107	DVLU	First Trust Dorsey Wright Momentum & Value ETF	1589	Multifactor	US
108	BMVP	Invesco Bloomberg MVP Multifactor ETF	5032	Multifactor	US
109	SPVM	Invesco S&P 500 Value with Momentum ETF	3407	Multifactor	US

ID	Ticker	Smart Beta ETF	Size	Category	Region
110	USVM	VictoryShares US Small Mid Cap Value Momentum ETF	1805	Multifactor	US
111	SPDV	AAM S&P 500 High Dividend Value ETF	1782	Multifactor	US
112	OUSA	ALPS O'Shares U.S. Quality Dividend ETF	2383	Multifactor	US
113	OUSM	ALPS O'Shares US Small-Cap Quality Dividend ETF	2012	Multifactor	US
114	FDRR	Fidelity Dividend ETF for Rising Rates	2086	Multifactor	US
115	QDEF	FlexShares Quality Dividend Defensive Index Fund	3027	Multifactor	US
116	QDF	FlexShares Quality Dividend Index Fund	3027	Multifactor	US
117	DIV	Global X SuperDividend US ETF	2972	Multifactor	US
118	SPHD	Invesco S&P 500 High Dividend Low Volatility ETF	3068	Multifactor	US
119	XSHD	Invesco S&P SmallCap High Dividend Low Volatility ETF	2032	Multifactor	US
120	DFND	Siren DIVCON Dividend Defender ETF	2255	Multifactor	US
121	LEAD	Siren DIVCON Leaders Dividend ETF	2261	Multifactor	US
122	VSDA	VictoryShares Dividend Accelerator ETF	1939	Multifactor	US
123	CDL	VictoryShares US Large Cap High Dividend Volatility Wtd ETF	2387	Multifactor	US
124	CSB	VictoryShares US Small Cap High Dividend Volatility Wtd ETF	2387	Multifactor	US
125	DGRW	WisdomTree US Quality Dividend Growth Fund	2922	Multifactor	US
126	DGRS	WisdomTree US Smallcap Quality Dividend Growth Fund	2878	Multifactor	US
127	B1YY1Y	Xtrackers Euro Stoxx Quality Dividend UCITS ETF	4417	Multifactor	US

ID	Ticker	Smart Beta ETF	Size	Category	Region
128	FLQL	Franklin U.S. Large Cap Multifactor Index ETF	1931	Multifactor	US
129	FLQM	Franklin U.S. Mid Cap Multifactor Index ETF	1931	Multifactor	US
130	FLQS	Franklin U.S. Small Cap Multifactor Index ETF	1931	Multifactor	US
131	VSMV	VictoryShares US Multi-Factor Minimum Volatility ETF	1893	Multifactor	US
132	DEUS	Xtrackers Russell US Multifactor ETF	2289	Multifactor	US
133	BLH969	Amundi MSCI Europe ESG Leaders Select UCITS ETF Capitalisation -UCITS ETF DR-	824	Multifactor	EU
134	BL6GBD	Deka MSCI EMU Climate Change ESG UCITS ETF Units	1124	Multifactor	EU
135	BZ1MDZ	Amundi MSCI Europe Minimum Volatility Factor	3724	Multifactor	EU
136	B2PJW5	Xtrackers SLI UCITS ETF Distribution 1D	4254	Multifactor	EU
137	BDZXK8	Franklin European Quality Dividend UCITS ETF	1840	Multifactor	EU
138	BK6KYK	iShares VI plc - iShares Edge MSCI Europe Minimum Volatility Advanced UCITS ETF AccumEUR	1181	Multifactor	EU
139	BL6GBC	Deka MSCI Europe Climate Change ESG UCITS ETF Units	1124	Multifactor	EU
140	GSEU	Goldman Sachs ActiveBeta Europe Equity ETF	2221	Multifactor	EU
141	BF7LG6	iShares MSCI Europe Quality Dividend ESG UCITS ETF	1873	Multifactor	EU
142	BD2MY3	WisdomTree Eurozone Quality Dividend Growth UCITS ETF EUR	2048	Multifactor	EU

ID	Ticker	Smart Beta ETF	Size	Category	Region
143	BD422F	WisdomTree Eurozone Quality Dividend Growth UCITS ETF EUR Acc	2130	Multifactor	EU
144	B1HPZL	Xtrackers Switzerland UCITS ETF Distribution 1D	4512	Multifactor	EU
145	B5YSGN	Amundi ETF MSCI Emu High Dividend UCITS ETF FCP	3984	Multifactor	EU
146	BDRXPL	XACT Nordic High Dividend Low Volatility (UCITS ETF)	1946	Multifactor	EU
147	BDVZYV	Xtrackers Switzerland UCITS ETF Capitalisation 1C	2835	Multifactor	EU
148	BN44VT	iShares Edge MSCI Europe Minimum Volatility Advanced UCITS ETF AccumHedged USD	1038	Multifactor	EU
149	BZ5ZCK	Invesco EURO STOXX High Dividend Low Volatility UCITS ETF	2259	Multifactor	EU
150	BFM2RT	UBS (Lux) Fund Solutions SICAV - UBS MSCI EMU Select Factor Mix UCITS ETF -(EUR) A-acc-Capitalisation	1633	Multifactor	EU
151	BQ2KCQ	Wisdomtree UK Quality Dividend Growth Ucits ETF Inc	277	Multifactor	EU
152	BQZJC6	WisdomTree Europe SmallCap Dividend UCITS ETF	2562	Multifactor	EU
153	BYQ7J9	WisdomTree Europe SmallCap Dividend UCITS ETF Acc	2048	Multifactor	EU
154	BG13YL	iShares Edge MSCI Europe Multifactor UCITS ETF	1721	Multifactor	EU
155	BYZ5QK	iShares Edge MSCI Europe Multifactor UCITS ETF	2343	Multifactor	EU
156	OEUR	ALPS O'Shares Europe Quality Dividend ETF	2357	Multifactor	EU
157	EUDG	WisdomTree Europe Quality Dividend Growth Fund	2681	Multifactor	EU

ID	Ticker	Smart Beta ETF	Size	Category	Region
158	B8X9NZ	First Trust United Kingdom AlphaDEX UCITS ETF Class A GBP	2958	Multifactor	EU
159	BD04H2	Landsbref - LEQ UCITS ETF	2863	Multifactor	EU
160	BF2FL5	First Trust Eurozone AlphaDEX UCITS ETF	1599	Multifactor	EU
161	BVF9N8	Ossiam Lux SICAV - Ossiam Shiller Barclay Cape Europe Sector Val TR Capitalisation -UCITS ETF 1C(EUR)-	2511	Multifactor	EU
162	BYXZHD	First Trust United Kingdom AlphaDEX UCITS ETF	2191	Multifactor	EU
163	B2QMYX	Deka STOXX Europe Strong Style Composite 40 UCITS ETF	4218	Multifactor	EU
164	FEP	First Trust Europe AlphaDEX Fund	3447	Multifactor	EU
165	FEUZ	First Trust Eurozone AlphaDEX ETF	2564	Multifactor	EU
166	FGM	First Trust Germany AlphaDEX Fund	3239	Multifactor	EU
167	FKU	First Trust United Kingdom AlphaDEX Fund	3239	Multifactor	EU
168	FSZ	First Trust Switzerland AlphaDEX Fund	3239	Multifactor	EU
169	B59GT4	UBS SXI Real Estate(R) Funds ETF Anteile -(CHF)-dis-	3810	Multifactor	EU
170	CBSE	Clough Select Equity ETF	1037	Volatility	US
171	FDLO	Fidelity Low Volatility Factor ETF	2086	Volatility	US
172	DIV	Global X SuperDividend US ETF	2972	Volatility	US
173	BUFF	Innovator Laddered Allocation Power Buffer ETF	2061	Volatility	US
174	SPMV	Invesco S&P 500 Minimum Variance ETF	1879	Volatility	US
175	XRLV	Invesco S&P 500 ex-Rate Sensitive Low Volatility ETF	2449	Volatility	US

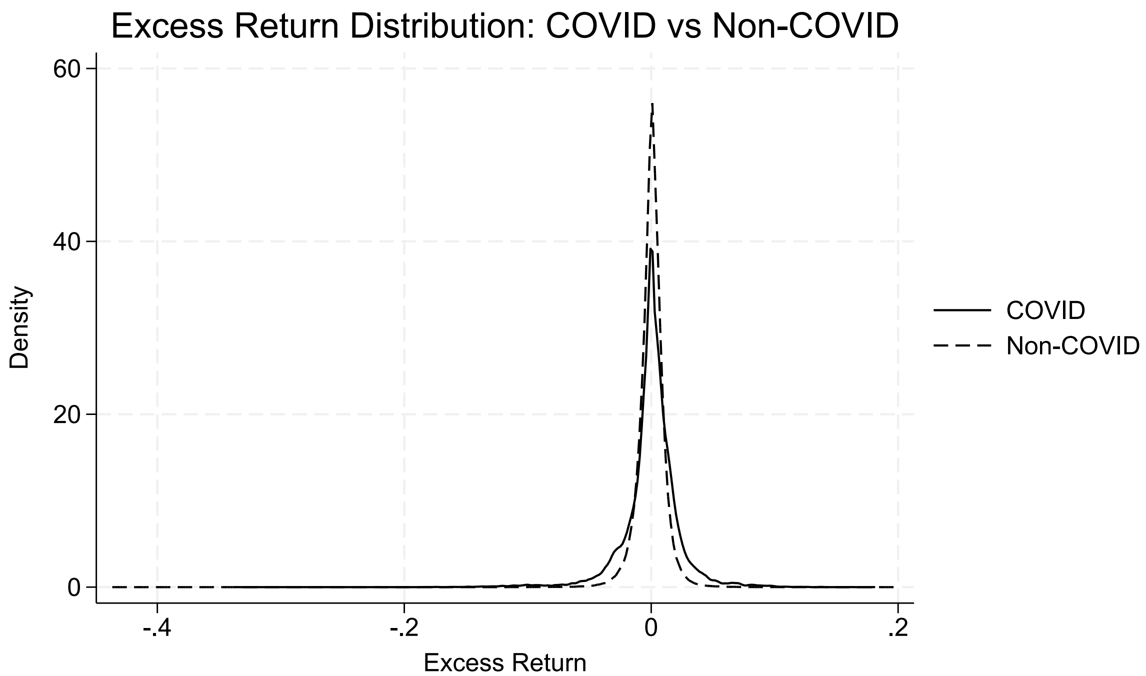
ID	Ticker	Smart Beta ETF	Size	Category	Region
176	SPLV	Invesco S&P 500 Low Volatility ETF	3436	Volatility	US
177	XMLV	Invesco S&P MidCap Low Volatility ETF	2988	Volatility	US
178	XSLV	Invesco S&P SmallCap Low Volatility ETF	2988	Volatility	US
179	USMV	iShares MSCI USA Min Vol Factor ETF	3319	Volatility	US
180	SMMV	iShares MSCI USA Small-Cap Min Vol Factor ETF	2090	Volatility	US
181	MSTB	LHA Market State Tactical Beta ETF	1069	Volatility	US
182	ONEV	SPDR Russell 1000 Low Volatility Focus ETF	2283	Volatility	US
183	LGLV	SPDR SSGA US Large Cap Low Volatility Index ETF	2985	Volatility	US
184	SMLV	SPDR SSGA US Small Cap Low Volatility Index ETF	2985	Volatility	US
185	THLV	THOR Equal Weight Low Volatility ETF	578	Volatility	US
186	VFMV	Vanguard U.S. Minimum Volatility ETF	1729	Volatility	US
187	*RWE.B	CI MSCI Europe Low Risk Weighted ETF	2300	Volatility	EU
188	*RWE	CI MSCI Europe Low Risk Weighted ETF Trust Units -Hedged-	2300	Volatility	EU
189	BYTLKQ	UBS (Lux) Fund Solutions SICAV - UBS Factor MSCI EMU Low Volatility UCITS ETF -(EUR) A-dis- Distribution	2333	Volatility	EU
190	BYYJC6	Factor MSCI EMU Low Volatility UCITS ETF (hedged to CHF) A-acc Capitalisation	1453	Volatility	EU

ID	Ticker	Smart Beta ETF	Size	Category	Region
191	BYYJC9	Factor MSCI EMU Low Volatility UCITS ETF (hedged to USD) A acc Capitalisation	1453	Volatility	EU
192	*RWE.A	First Asset MSCI Europe Low Risk Weighted ETF Advisor Units	862	Volatility	EU
193	*RWE.D	First Asset MSCI Europe Low Risk Weighted ETF Unhedged Advisor Units	862	Volatility	EU
194	BRWQVY	Invesco RBIS Equal Risk Equity Europe UCITS ETF	1000	Volatility	EU
195	B86MWN	iShares Edge MSCI Europe Minimum Volatility UCITS ETF	3039	Volatility	EU
196	BG13YK	iShares Edge MSCI Europe Minimum Volatility UCITS ETF	1721	Volatility	EU
197	HEUV	iShares Edge MSCI Min Vol Europe Currency Hedged ETF	763	Volatility	EU
198	EUMV	iShares Edge MSCI Min Vol Europe ETF	1561	Volatility	EU
199	BYVHWR	Lyxor FTSE EMU Minimum Variance UCITS ETF	660	Volatility	EU
200	BYM106	Lyxor FTSE Europe Minimum Variance (DR) UCITS ETF	1521	Volatility	EU
201	FXEU	PowerShares Europe Currency Hedged Low Volatility Portfolio	664	Volatility	EU
202	BGLCD0	SPDR EURO STOXX Low Volatility UCITS ETF EUR	2711	Volatility	EU
-	MTUM	iShares MSCI USA Momentum Factor ETF	2946	Benchmark	US
-	DVY	iShares Select Dividend ETF	5033	Benchmark	US
-	SPLV	Invesco S&P 500 Low Volatility ETF	3436	Benchmark	US
-	SPY	SPDR S&P 500 ETF Trust	5033	Benchmark	US
-	MMTM	SPDR S&P 1500 Momentum Tilt ETF	3063	Benchmark	*US/EU*

ID	Ticker	Smart Beta ETF	Size	Category	Region
-	EUDIV-FR	Multi Units Luxembourg SICAV - Amundi S&P Eurozone Dividend Aristocrat Screened -Dist- Distribution	2834	Benchmark	EU
-	ZPRL-DE	SPDR EURO STOXX Low Volatility UCITS ETF EUR	2711	Benchmark	EU
-	EXSA-DE	iShares STOXX Europe 600 UCITS ETF	4965	Benchmark	EU

Note: This table lists all Smart Beta ETFs grouped by investment strategy (Category) and Region. Sample size refers to the number of return observations from 2005 to 2024. An asterisk (*) marks ETFs that have a hedged and unhedged version; testing revealed no significant difference between them. The italicized entry marks the benchmark ETF that covers both the US and EU markets, due to the absence of a suitable broad momentum strategy in Europe.

Fig. A.2: Excess Return Distribution:COVID-19



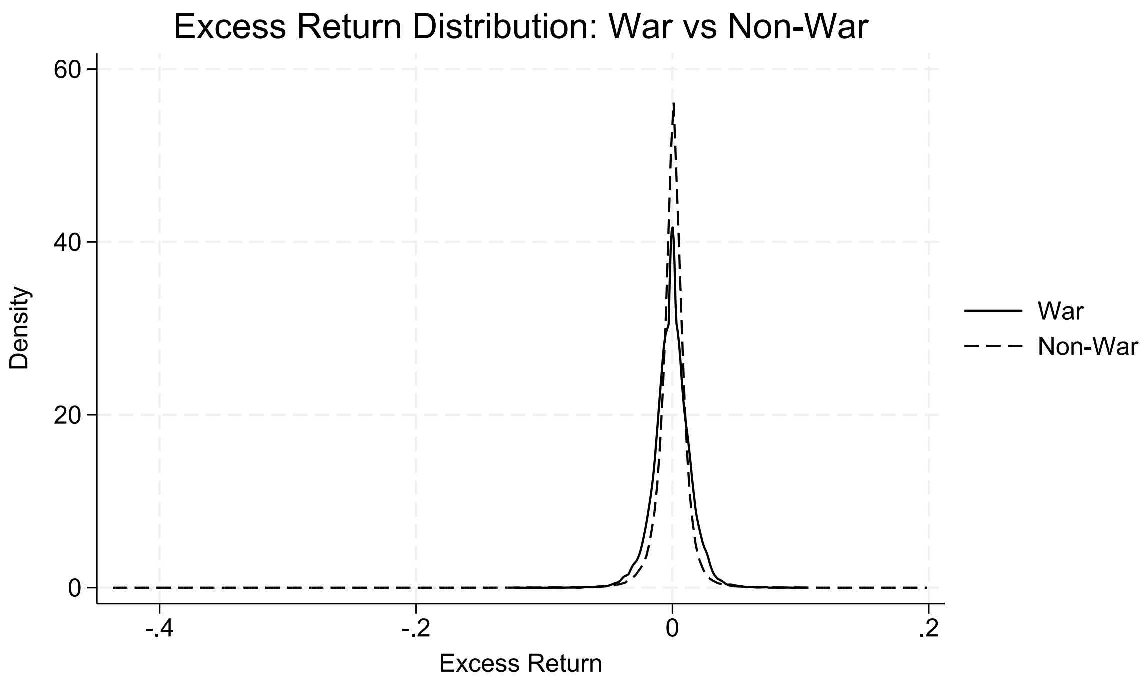
Note: This density plot compares the distribution of daily excess returns during the COVID-19 period (Feb-Dec 2020) with non-COVID periods. It illustrates how return dynamics shifted under pandemic-related market stress.

Table A.3: Hausman test: Factor model results for each Smart Beta ETF category

Model	**Strategy**	**All**	**US**	**EU**
Fama French 3-Factor	Momentum	0.1294	0.5163	0.6081
	Dividend	0.1364	0.6552	0.1243
	Low Volatility	0.5496	0.9726	0.9358
	Multifactor	0.0468	0.2786	0.8449
Carhart 4-Factor	Momentum	0.2754	0.6645	0.5549
	Dividend	0.2232	0.3229	0.1502
	Low Volatility	0.2613	0.9921	0.2700
	Multifactor	0.0797	0.3544	0.7238
Fama French 5-Factor	Momentum	0.1506	0.7276	0.5818
	Dividend	0.0841	0.5589	0.0743
	Low Volatility	0.6763	0.6657	0.9165
	Multifactor	0.0192	0.5493	0.9456
Extended 6-Factor	Momentum	0.1506	0.7276	0.5818
	Dividend	0.0841	0.5589	0.0743
	Low Volatility	0.6763	0.6657	0.9165
	Multifactor	0.0192	0.5493	0.9456

Note: This table reports p-values from the Hausman specification test, applied to Smart Beta ETFs across four different factor models: Fama French 3-Factor, Carhart 4-Factor, Fama French 5-Factor, and an Extended 6-Factor model. Results are provided for four strategy categories (momentum, dividend, low volatility, and multifactor), and for three sample regions: the full sample (All), US-only, and EU-only. Lower p-values indicate a rejection of the null hypothesis that the random effects model is consistent, favoring fixed effects.

Fig. A.3: Excess Return Distribution: Russia-Ukraine War



Note: This density plot compares the distribution of daily excess returns during the war period (Feb-Dec 2022) with non-war periods. It illustrates how return dynamics shifted under crisis-related market stress.

Table A.4: COVID-19: Model Diagnostics for Factor Regressions by Strategy and Region

	Strategy	**VIF**			**Wooldridge**			**Root MSE**		
		All	US	EU	All	US	EU	All	US	EU
FF3	Momentum	1.84	1.83	1.45	0.0036	0.0026	0.0365	0.0125	0.0132	0.0066
	Dividend	2.16	2.24	2.28	0.0057	0.0034	0.1530	0.0123	0.0130	0.0063
	Low Vol	2.00	2.04	2.22	0.0041	0.0036	0.0477	0.0125	0.0132	0.0066
	Multif.	2.30	2.45	2.96	0.0060	0.0038	0.2662	0.0123	0.0130	0.0062
C4	Momentum	1.94	1.91	1.89	0.6466	0.0325	0.8044	0.0103	0.0083	0.0119
	Dividend	2.04	2.12	2.04	0.6337	0.0502	0.8034	0.0103	0.0082	0.0119
	Low Vol	1.99	2.01	2.04	0.6823	0.0616	0.8319	0.0102	0.0082	0.0119
	Multif.	2.03	2.24	2.22	0.6846	0.0987	0.8235	0.0102	0.0081	0.0119
FF5	Momentum	6.85	6.38	1.66	0.2051	0.0204	0.0103	0.0094	0.0089	0.0091
	Dividend	6.92	6.62	2.05	0.1850	0.0194	0.0102	0.0090	0.0089	0.0090
	Low Vol	6.65	6.17	2.04	0.1989	0.0229	0.0096	0.0089	0.0088	0.0091
	Multif.	6.73	6.45	2.45	0.1786	0.0215	0.0121	0.0093	0.0088	0.0090
6F	Momentum	1.90	1.88	2.30	0.0415	0.6382	0.0036	0.0090	0.0100	0.0112
	Dividend	2.00	2.16	2.43	0.0373	0.6367	0.0027	0.0108	0.0100	0.0112
	Low Vol	1.95	2.02	2.41	0.0446	0.6437	0.0034	0.0108	0.0099	0.0112
	Multif.	1.98	2.31	2.58	0.0403	0.6386	0.0028	0.0108	0.0100	0.0112

Note: This provides diagnostic results for factor regressions estimated in the COVID-19 period, separately by smart beta strategy (momentum, dividend, low volatility, multifactor) and region (All, US, EU). The reported statistics include three metrics: the Variance Inflation Factor (VIF), the Wooldridge test p-values for autocorrelation, and the Root Mean Squared Error (Root MSE). VIF values exceeding 5 may indicate potential collinearity issues. The Wooldridge test: lower p-values suggest stronger evidence of autocorrelation. Root MSE: lower values indicate better model fit.

Table A.5: COVID-19: Model Diagnostics for Factor Regressions by Strategy and Region

	Strategy	VIF			Wooldridge			Root MSE		
		All	US	EU	All	US	EU	All	US	EU
FF3	Momentum	1.83	1.83	1.32	0.0833	0.0026	0.7680	0.0096	0.0132	0.0069
	Dividend	1.92	2.24	1.64	0.2036	0.0034	0.5399	0.0091	0.0130	0.0064
	Low Vol	2.18	2.04	2.07	0.0860	0.0036	0.8671	0.0096	0.0132	0.0068
	Multif.	2.23	2.45	2.23	0.1796	0.0038	0.8557	0.0091	0.0130	0.0063
C4	Momentum	1.94	1.90	1.88	0.0078	0.1318	0.0022	0.0073	0.0051	0.0085
	Dividend	1.96	1.96	1.92	0.0078	0.0417	0.0035	0.0073	0.0050	0.0085
	Low Vol	2.03	2.14	2.00	0.0062	0.0652	0.0031	0.0073	0.0049	0.0085
	Multif.	2.03	2.18	2.04	0.0062	0.0312	0.0048	0.0073	0.0048	0.0085
FF5	Momentum	1.88	1.76	1.47	0.0022	0.0254	0.0019	0.0085	0.0062	0.0066
	Dividend	1.92	1.89	1.71	0.0035	0.0249	0.0015	0.0085	0.0062	0.0066
	Low Vol	2.00	2.27	2.04	0.0031	0.0487	0.0026	0.0085	0.0060	0.0066
	Multif.	2.04	2.36	2.17	0.0048	0.0535	0.0021	0.0085	0.0060	0.0067
6F	Momentum	1.93	1.87	1.88	0.0009	0.0021	0.0021	0.0086	0.0063	0.0098
	Dividend	1.88	1.85	1.96	0.0009	0.0019	0.0008	0.0086	0.0063	0.0098
	Low Vol	2.03	2.18	2.00	0.0010	0.0006	0.0006	0.0086	0.0062	0.0098
	Multif.	2.04	2.19	2.04	0.0010	0.0006	0.0012	0.0086	0.0062	0.0098

Note: This provides diagnostic results for factor regressions estimated in the Russia-Ukraine war period, separately by smart beta strategy (momentum, dividend, low volatility, multifactor) and region (All, US, EU). The reported statistics include three metrics: the Variance Inflation Factor (VIF), the Wooldridge test p-values for autocorrelation, and the Root Mean Squared Error (Root MSE). VIF values exceeding 5 may indicate potential collinearity issues. The Wooldridge test: lower p-values suggest stronger evidence of autocorrelation. Root MSE: lower values indicate better model fit.

Table A.6: Six-Factor Model with COVID-19 Interactions for Smart Beta ETFs: Momentum, Dividend, Volatility, and Multifactor Strategies

Term	**Momentum**		**Dividend**		**Volatility**		**Multifactor**	
	US	**EU**	**US**	**EU**	**US**	**EU**	**US**	**EU**
MRP	0.9849***	0.6733***	0.8911***	0.5676***	0.7364***	0.4463***	0.8329***	0.6247***
	(0.0436)	*(0.0139)*	*(0.0129)*	*(0.0214)*	*(0.0182)*	*(0.0295)*	*(0.0378)*	*(0.0481)*
ΔC–19 Intercept	-0.0005**	-0.0002**	-0.0002***	-0.0002**	-0.0005***	-0.0004***	-0.0003***	-0.0002**
	(0.0001)	*(0.0000)*	*(0.0001)*	*(0.0001)*	*(0.0001)*	*(0.0001)*	*(0.00005)*	*(0.0001)*
ΔC–19 × MRP	0.0167	0.2276***	0.0855***	0.2467***	0.1763***	0.2760***	0.0792***	0.2028***
	(0.0357)	*(0.0209)*	*(0.0125)*	*(0.0269)*	*(0.0261)*	*(0.0264)*	*(0.0241)*	*(0.0288)*
SMB	0.3794***	-0.4865***	0.1421**	-0.3868***	0.1509*	-0.4552***	0.2474***	-0.1231*
	(0.0776)	*(0.0448)*	*(0.0506)*	*(0.0462)*	*(0.0866)*	*(0.0447)*	*(0.0656)*	*(0.0608)*
ΔC–19 × SMB	0.0775	0.1608***	-0.0451	0.2661***	0.0921**	0.3153***	0.0611	0.1043
	(0.0453)	*(0.0131)*	*(0.0324)*	*(0.0711)*	*(0.0419)*	*(0.0770)*	*(0.0386)*	*(0.0695)*
HML	-0.0077	-0.0777***	0.2381***	0.1785***	0.0340	-0.2030***	0.1203***	-0.0148
	(0.1123)	*(0.0130)*	*(0.0265)*	*(0.0355)*	*(0.0303)*	*(0.0390)*	*(0.0300)*	*(0.0614)*
ΔC–19 × HML	0.0722	-0.1599	-0.0828	0.0977	0.2845***	0.2600**	0.0563	0.1819*
	(0.0685)	*(0.1746)*	*(0.0517)*	*(0.0698)*	*(0.0829)*	*(0.0940)*	*(0.0554)*	*(0.0918)*
RMW	-0.0329	-0.1615**	0.1164***	-0.0532	0.1358***	0.1039***	0.2022***	-0.0332
	(0.0682)	*(0.0398)*	*(0.0252)*	*(0.0359)*	*(0.0316)*	*(0.0349)*	*(0.0227)*	*(0.0457)*
ΔC–19 × RMW	-0.1696*	0.2125	-0.2086***	0.0851	-0.1440**	-0.0439	-0.1210**	0.0473
	(0.0976)	*(0.1061)*	*(0.0477)*	*(0.0576)*	*(0.0532)*	*(0.0548)*	*(0.0459)*	*(0.0898)*
CMA	-0.0015	-0.3410***	0.2141***	-0.1712***	0.2152***	-0.0225	0.1355***	-0.1315***
	(0.0804)	*(0.0405)*	*(0.0298)*	*(0.0336)*	*(0.0413)*	*(0.0672)*	*(0.0363)*	*(0.0474)*

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Term	**Momentum**		**Dividend**		**Volatility**		**Multifactor**	
	US	**EU**	**US**	**EU**	**US**	**EU**	**US**	**EU**
ΔC–19 × CMA	0.0051	0.8034***	0.1726***	0.5034***	-0.1269	0.3661***	0.0557	0.1575*
	(0.0745)	*(0.0381)*	*(0.0522)*	*(0.0829)*	*(0.0991)*	*(0.0861)*	*(0.0545)*	*(0.0802)*
WML	0.2207***	0.3741***	-0.1090***	-0.0853***	-0.0146	0.0160	-0.0211	-0.0097
	(0.0347)	*(0.0442)*	*(0.0118)*	*(0.0132)*	*(0.0107)*	*(0.0161)*	*(0.0181)*	*(0.0123)*
ΔC–19 × WML	0.0715	-0.0681	-0.0390	0.1088***	0.1331**	0.1731**	0.0754*	0.1179***
	(0.0745)	*(0.0792)*	*(0.0309)*	*(0.0349)*	*(0.0470)*	*(0.0691)*	*(0.0394)*	*(0.0407)*
Constant	-0.0002***	-0.0001*	-0.0001***	-0.00001	-0.0001**	0.0001***	-0.0001***	0.00009***
	(0.00002)	*(0.00003)*	*(0.00001)*	*(0.00001)*	*(0.00002)*	*(0.00001)*	*(0.00002)*	*(0.00002)*

Note: This table reports results from an extended six-factor model including MRP (Market), SMB (Size), HML (Value), RMW (Profitability), CMA (Investment), and WML (Momentum), each interacted with a COVID-19 dummy. Results are reported for Smart Beta ETFs across four strategy types (Momentum, Dividend, Volatility, and Multifactor) in both the US and EU. Robust standard errors in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.7: Six-Factor Model with Russia-Ukraine War Interactions for Smart Beta ETFs: Momentum, Dividend, Volatility, and Multifactor Strategies

Term	**Momentum**		**Dividend**		**Volatility**		**Multifactor**	
	US	**EU**	**US**	**EU**	**US**	**EU**	**US**	**EU**
MRP	0.9837***	0.7713***	0.9099***	0.6450***	0.8194***	0.5413***	0.8603***	0.6856***
	(0.0362)	(0.0150)	(0.0120)	(0.0206)	(0.0160)	(0.0315)	(0.0329)	(0.0470)
War Intercept	0.0000	-0.0000	0.0000	-0.0001***	0.0000	-0.0002**	-0.00004	-0.00023***
	(0.0001)	(0.0001)	(0.00003)	(0.00004)	(0.00005)	(0.00007)	(0.00004)	(0.00005)
War × MRP	0.0863***	-0.1200**	0.0045	-0.1151***	-0.0632**	-0.1075***	0.0297	-0.0507**
	(0.0253)	(0.0210)	(0.0137)	(0.0240)	(0.0254)	(0.0352)	(0.0176)	(0.0217)
SMB	0.3931***	-0.4599***	0.1389***	-0.3002***	0.1707*	-0.3538***	0.2594***	-0.0662
	(0.0804)	(0.0479)	(0.0511)	(0.0471)	(0.0904)	(0.0510)	(0.0682)	(0.0605)
War × SMB	0.1250**	0.0051	0.0538*	-0.0239	0.0220	-0.1134	0.0458**	-0.1543***
	(0.0516)	(0.0252)	(0.0291)	(0.0594)	(0.0480)	(0.0781)	(0.0176)	(0.0500)
HML	-0.0214	-0.0370	0.2310***	0.1890***	0.1108***	-0.0590	0.1396***	0.0151
	(0.1150)	(0.0387)	(0.0258)	(0.0353)	(0.0376)	(0.0522)	(0.0344)	(0.0600)
War × HML	0.1184*	-0.1377**	-0.0185	-0.0156	-0.1812***	-0.1741***	-0.0614**	0.0291
	(0.0603)	(0.0262)	(0.0192)	(0.0424)	(0.0288)	(0.0465)	(0.0237)	(0.0431)
RMW	-0.0391	0.0092	0.1090***	0.0474	0.1677***	0.2830***	0.2090***	0.0447
	(0.0758)	(0.0659)	(0.0287)	(0.0415)	(0.0298)	(0.0431)	(0.0201)	(0.0471)
War × RMW	0.0021	-0.2932**	0.0755**	-0.1853***	0.0131	-0.3381***	0.0143	-0.0632
	(0.0933)	(0.0701)	(0.0304)	(0.0460)	(0.0275)	(0.0787)	(0.0264)	(0.0538)
CMA	-0.0069	-0.1700**	0.2345***	-0.0642*	0.1875***	0.0361	0.1375***	-0.0622
	(0.0928)	(0.0479)	(0.0326)	(0.0348)	(0.0432)	(0.0765)	(0.0371)	(0.0570)

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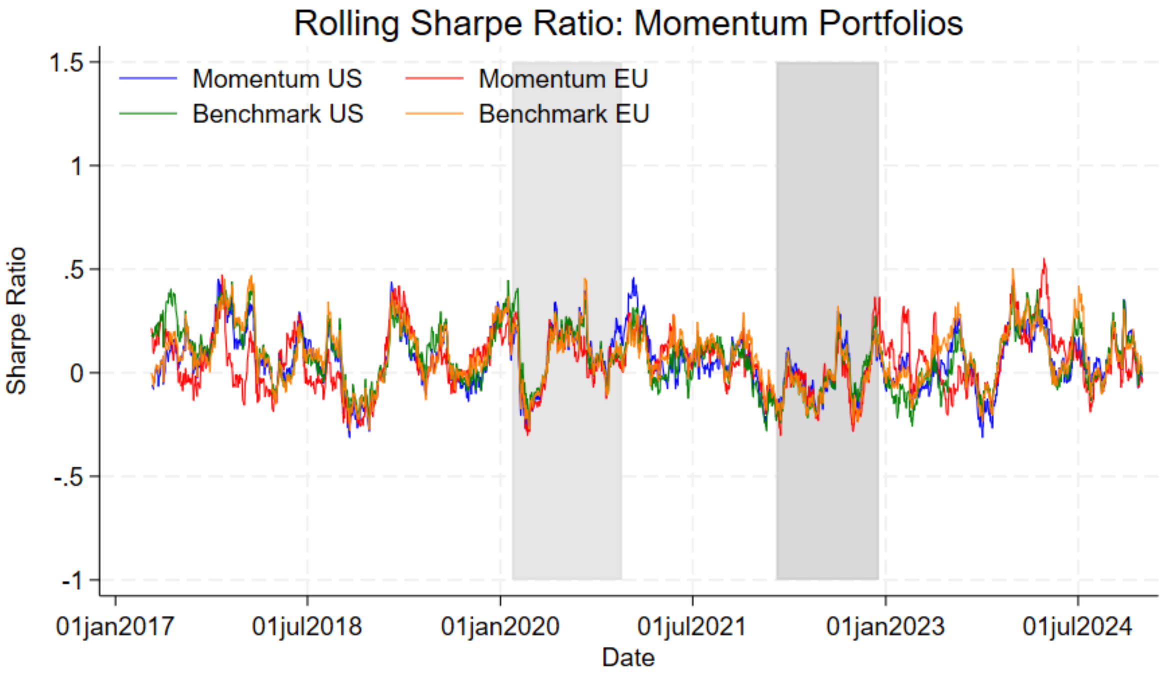
Term	Momentum		Dividend		Volatility		Multifactor	
	US	**EU**	**US**	**EU**	**US**	**EU**	**US**	**EU**
War × CMA	-0.1189*	-0.0965	0.0416	-0.0324	0.1315**	-0.0307	0.0841***	-0.0398
	(0.0700)	(0.0661)	(0.0269)	(0.0388)	(0.0608)	(0.1203)	(0.0281)	(0.0605)
WML	0.2068***	0.3076***	-0.1138***	-0.1162***	-0.0159	0.0216	-0.0102	-0.0201
	(0.0283)	(0.0364)	(0.0123)	(0.0165)	(0.0115)	(0.0157)	(0.0189)	(0.0136)
War × WML	0.1493***	0.0819***	0.0192	0.0531*	0.0319*	-0.0367	0.0103	-0.0051
	(0.0492)	(0.0132)	(0.0176)	(0.0277)	(0.0181)	(0.0557)	(0.0101)	(0.0292)
Constant	-0.0003***	-0.0001***	-0.0001***	-0.00004***	-0.0001***	0.00001	-0.0001***	0.00007***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00002)	(0.00001)	(0.00002)	(0.00002)

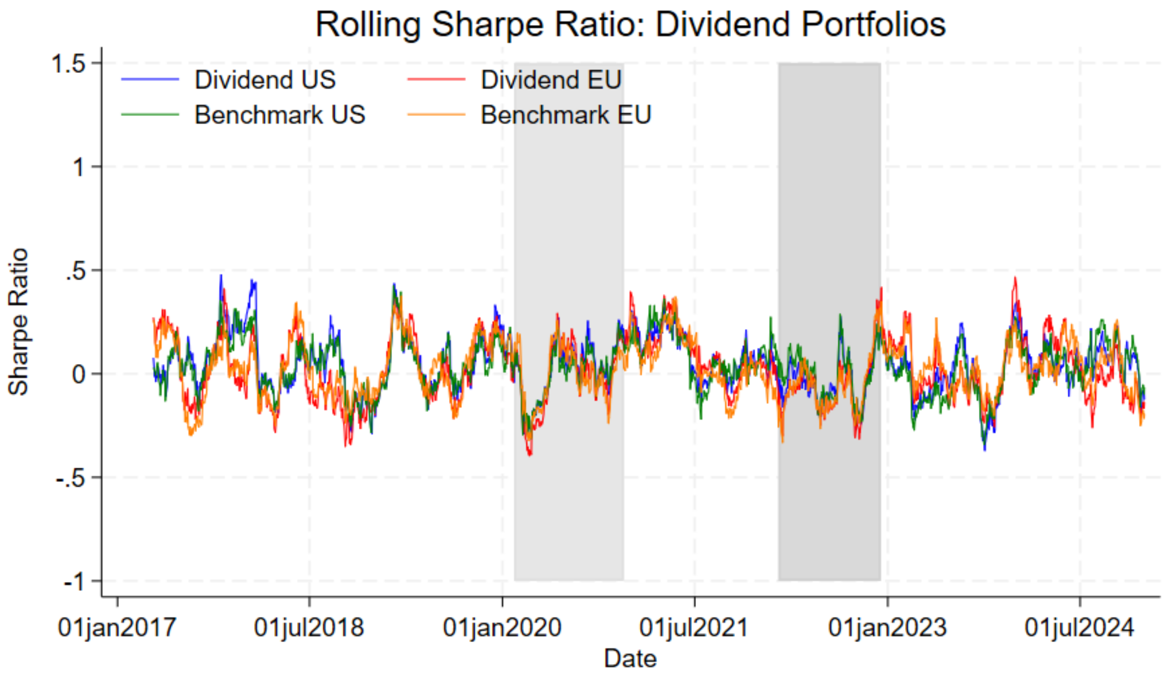
Note: This table reports results from a six-factor model including MRP (Market), SMB (Size), HML (Value), RMW (Profitability), CMA (Investment), and WML (Momentum), each interacted with a dummy variable capturing the Russia-Ukraine war period. Results are reported for Smart Beta ETFs across four strategy types (momentum, dividend, volatility, and multifactor) in both the US and EU. Robust standard errors in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Fig. A.4: Rolling Sharpe Ratio Momentum US vs. EU



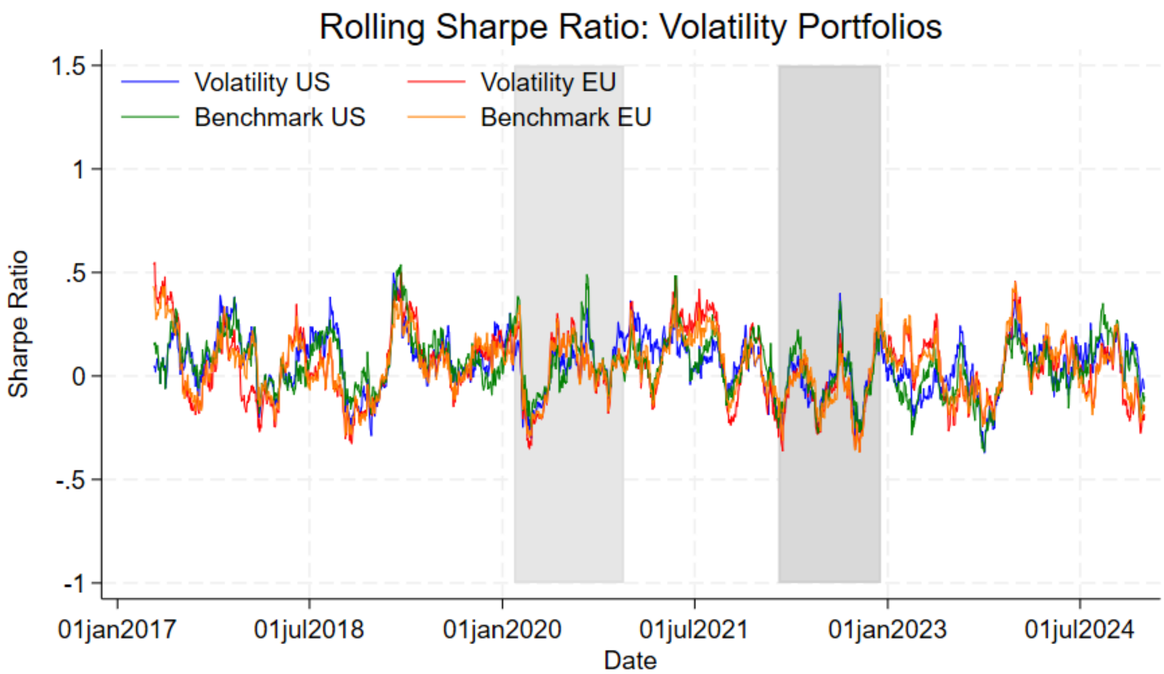
Note: This figure compares the performance stability of Momentum Smart Beta (EU and US) portfolios using 63-day rolling Sharpe Ratios. Gray shaded areas indicate our major crisis periods, COVID-19 and Russia-Ukraine war.

Fig. A.5: Rolling Sharpe Ratio Dividend US vs. EU



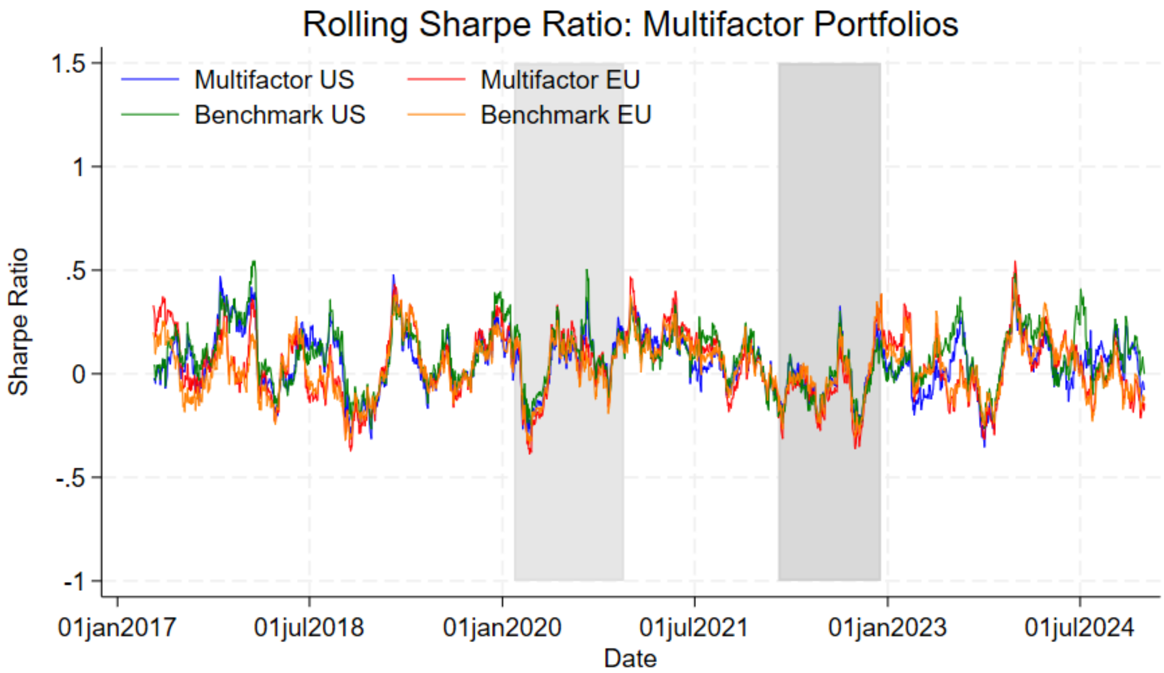
Note: This figure compares the performance stability of Dividend Smart Beta (EU and US) portfolios using 63-day rolling Sharpe Ratios. Gray shaded areas indicate our major crisis periods, COVID-19 and Russia-Ukraine war.

Fig. A.6: Rolling Sharpe Ratio Volatility US vs. EU



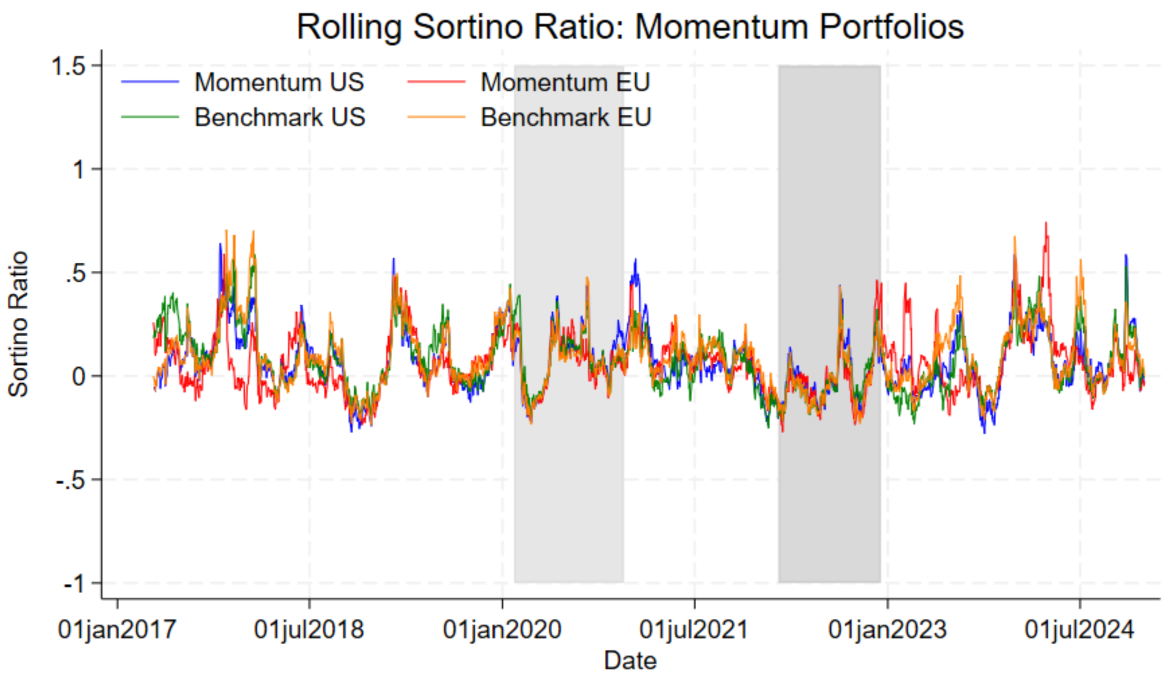
Note: This figure compares the performance stability of Low Volatility Smart Beta (EU and US) portfolios using 63-day rolling Sharpe Ratios. Gray shaded areas indicate our major crisis periods, COVID-19 and Russia-Ukraine war.

Fig. A.7: Rolling Sharpe Ratio Multifactor US vs. EU



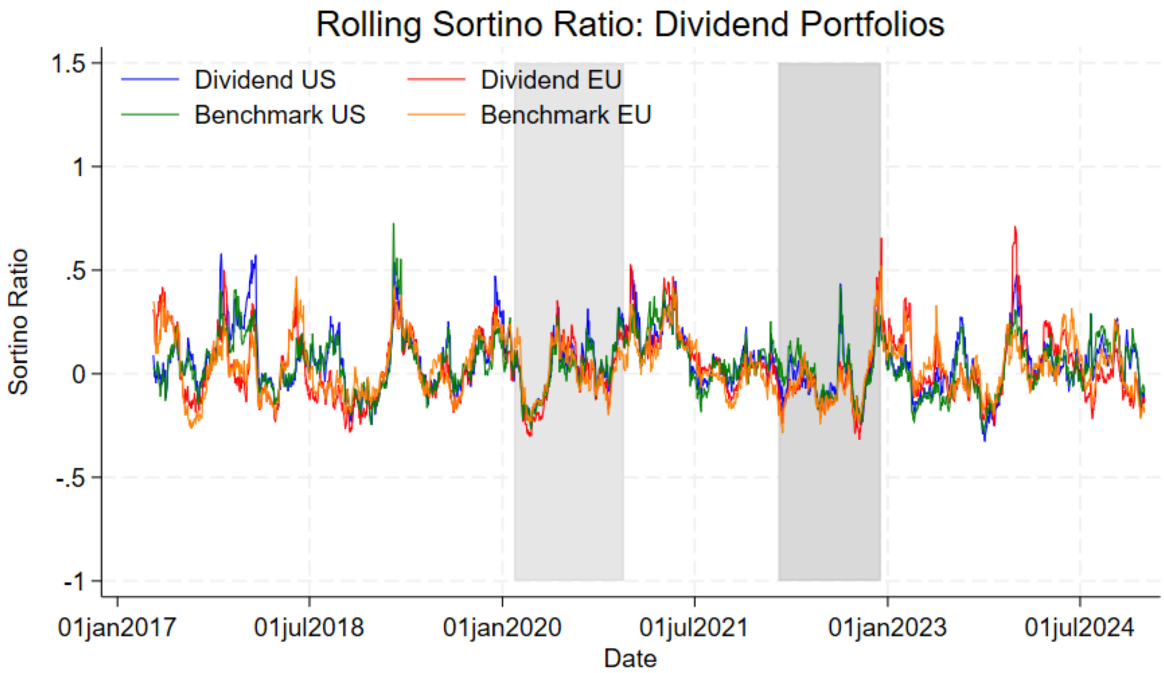
Note: This figure compares the performance stability of Multifactor Smart Beta (EU and US) portfolios using 63-day rolling Sharpe Ratios. Gray shaded areas indicate our major crisis periods, COVID-19 and Russia-Ukraine war.

Fig. A.8: Rolling Sortino Ratio Momentum US vs. EU



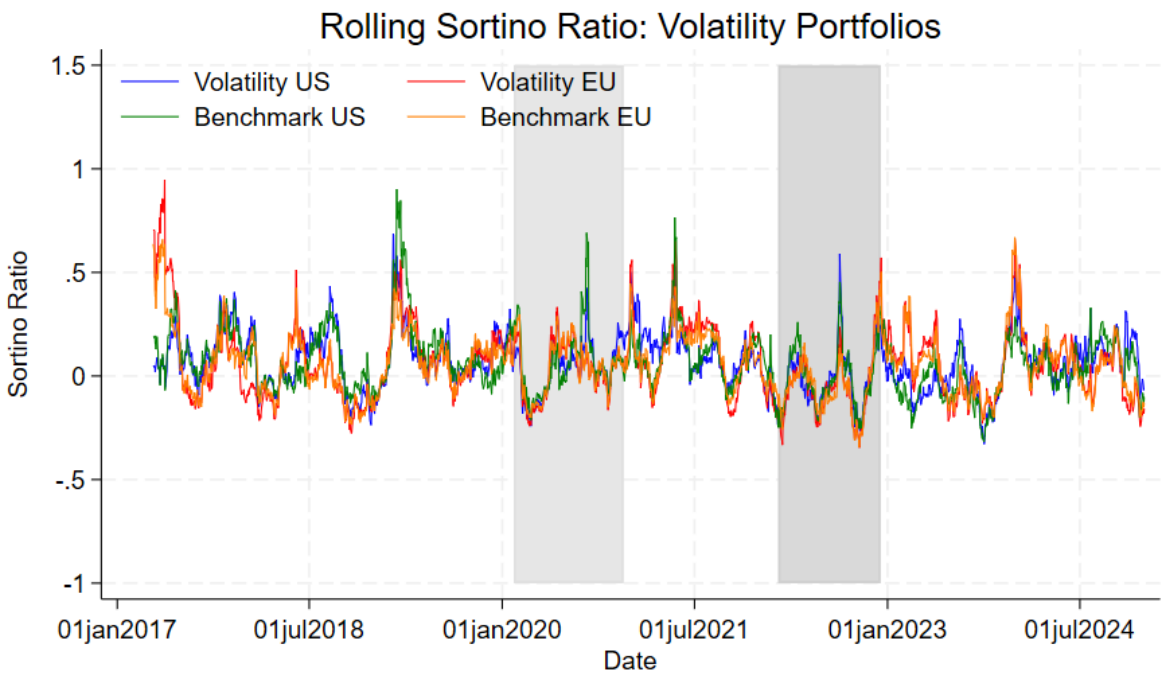
Note: This figure compares the performance stability of Momentum Smart Beta (EU and US) portfolios using 63-day rolling Sortino Ratios. Gray shaded areas indicate our major crisis periods, COVID-19 and Russia-Ukraine war.

Fig. A.9: Rolling Sortino Ratio Dividend US vs. EU



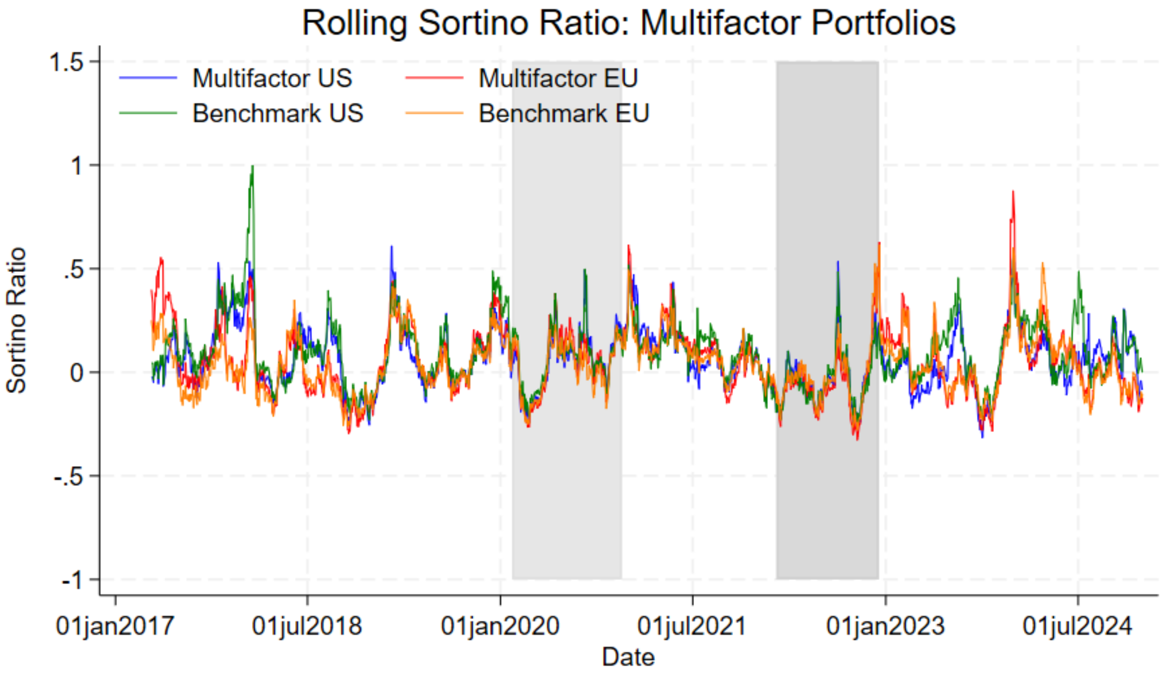
Note: This figure compares the performance stability of Dividend Smart Beta (EU and US) portfolios using 63-day rolling Sortino Ratios. Gray shaded areas indicate our major crisis periods, COVID-19 and Russia-Ukraine war.

Fig. A.10: Rolling Sortino Ratio Volatility US vs. EU



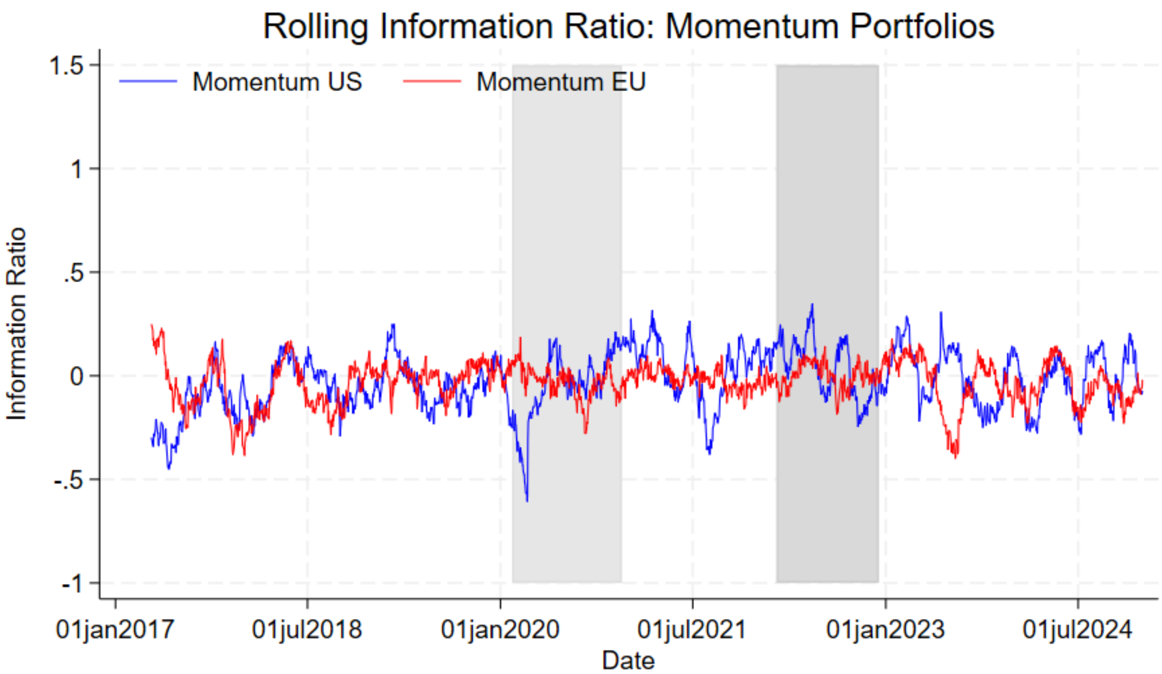
Note: This figure compares the performance stability of Low Volatility Smart Beta (EU and US) portfolios using 63-day rolling Sortino Ratios. Gray shaded areas indicate our major crisis periods, COVID-19 and Russia-Ukraine war.

Fig. A.11: Rolling Sharpe Ratio Multifactor US vs. EU



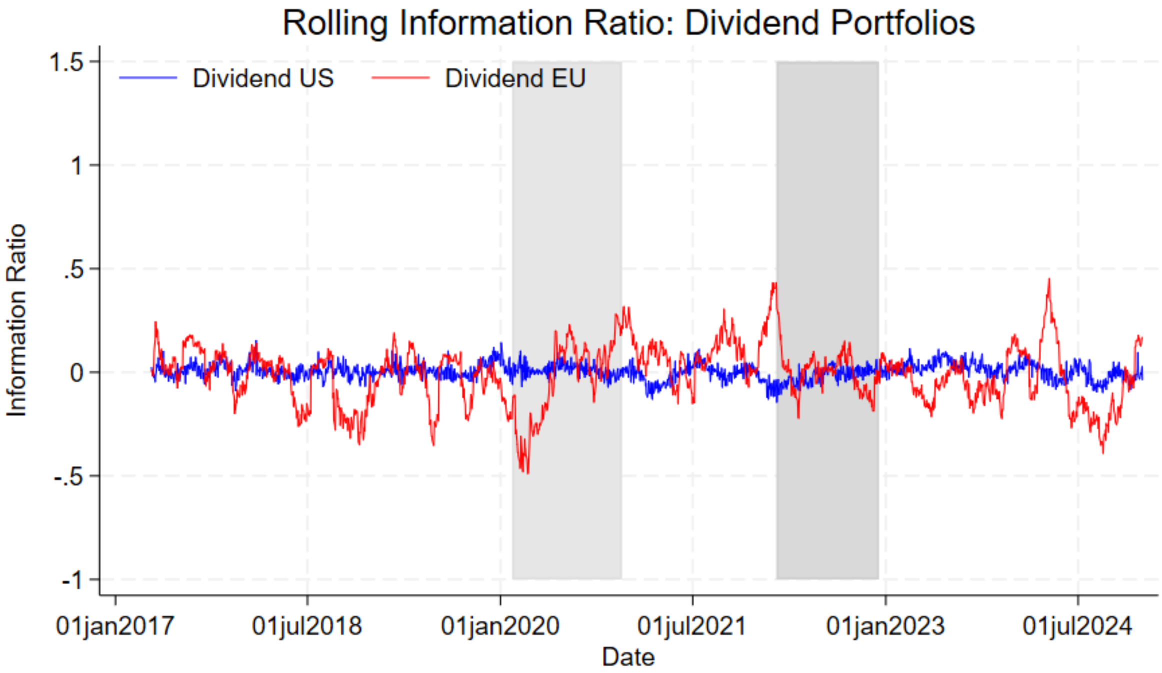
Note: This figure compares the performance stability of Multifactor Smart Beta (EU and US) portfolios using 63-day rolling Sortino Ratios. Gray shaded areas indicate our major crisis periods, COVID-19 and Russia-Ukraine war.

Fig. A.12: Rolling Information Ratio Momentum US vs. EU



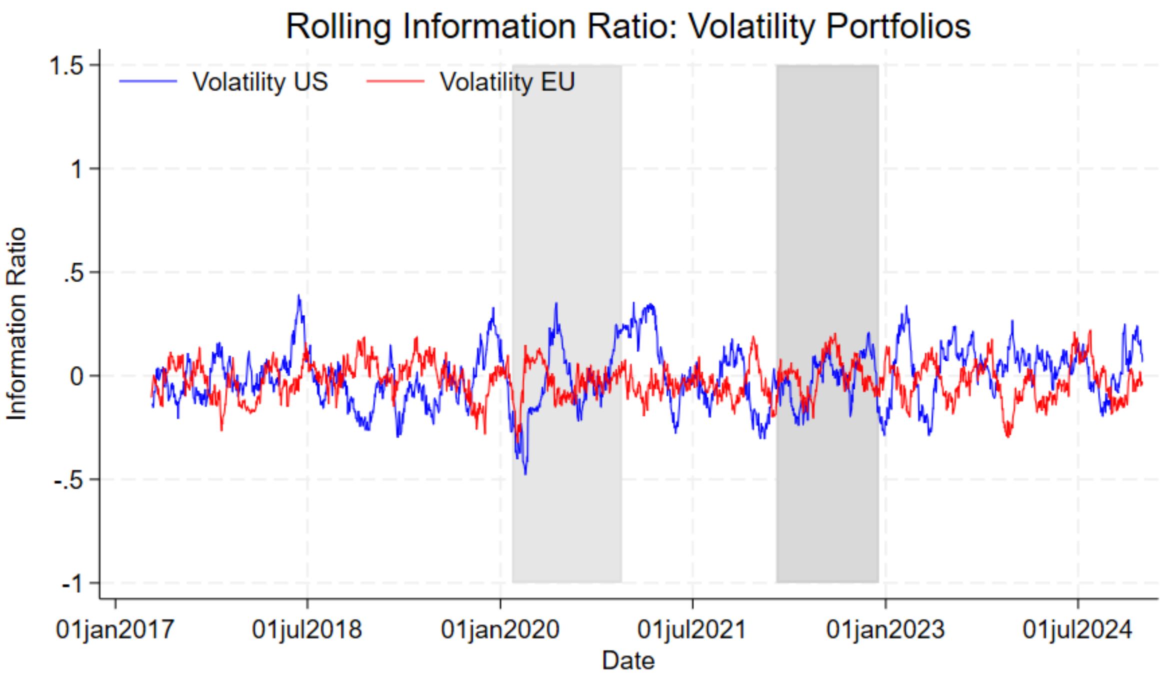
Note: This figure compares the performance stability of Momentum Smart Beta (EU and US) portfolios using 63-day rolling Information Ratios. Gray shaded areas indicate our major crisis periods, COVID-19 and Russia-Ukraine war.

Fig. A.13: Rolling Information Ratio Dividend US vs. EU



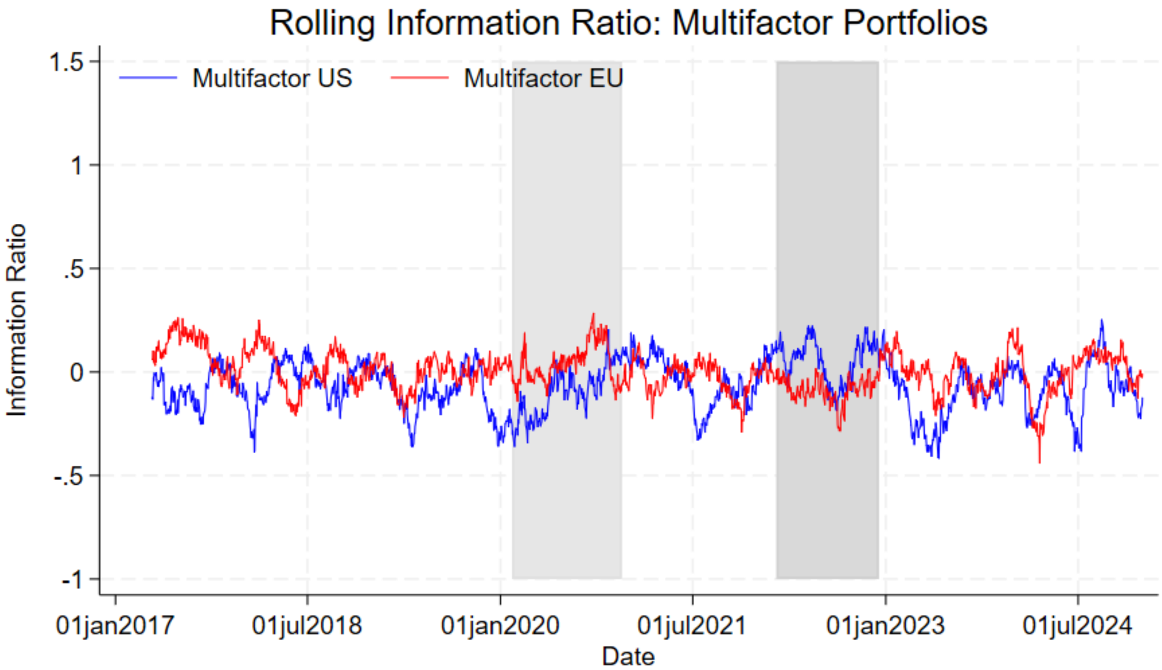
Note: This figure compares the performance stability of Dividend Smart Beta (EU and US) portfolios using 63-day rolling Information Ratios. Gray shaded areas indicate our major crisis periods, COVID-19 and Russia-Ukraine war.

Fig. A.14: Rolling Information Ratio Volatility US vs. EU



Note: This figure compares the performance stability of Low Volatility Smart Beta (EU and US) portfolios using 63-day rolling Information Ratios. Gray shaded areas indicate our major crisis periods, COVID-19 and Russia-Ukraine war.

Fig. A.15: Rolling Information Ratio Multifactor US vs. EU



Note: This figure compares the performance stability of Multifactor Smart Beta (EU and US) portfolios using 63-day rolling Information Ratios. Gray shaded areas indicate our major crisis periods, COVID-19 and Russia-Ukraine war.

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AI Usage Statement

In the preparation of this thesis, generative AI tools such as *ChatGPT* were used in accordance with Aalborg University's guidelines for responsible academic use of AI. Specifically, AI was used to:

- Explore relevant theorists, methods, and analytical approaches related to the research topic,
- Evaluate the applicability of specific theories to the study,
- Support early-stage idea generation and brainstorming,
- Assist with LaTeX formatting for tables and graphs,
- Provide support in understanding, fixing and simplifying `STATA` code used for data processing and analysis.

All AI-assisted suggestions and outputs were critically assessed and verified through academic literature, database searches, notably Primo, and independent analysis. The `STATA` code and theoretical applications presented are the result of my own work, with AI used only as a supplementary tool for loops and simplification.