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Master Thesis Financial Economics

Enhancing Factor Investing for European Corporate Bonds: The ESG Perspective

Name student: João Sousa

Student ID number: 643729

Supervisor: Esad Smajlbegovic

Second assessor:

Date final version:

Abstract

This study examines factor investing in the European corporate bond market, focusing on five key factors: *ESG (Environmental, social, and corporate governance), Size, Value, Low-Risk, and Momentum*. Utilizing the Capital Asset Pricing Model (CAPM) and a Six-Factor Model, the research analyzes a dataset of bonds issued by the issuers listed in the Stoxx 600. The study reveals that the CAPM model showed statistically non-significant alphas for all factors, with the alphas generally higher in the long portfolios than in the long-short portfolios, except for *Momentum.* The Six-Factor Model shows in general lower alphas than the CAPM. During the COVID-19 crisis, the research functions as a stress test, highlighting that long-short portfolios generally outperformed their long-only counterparts. Specifically, the ESG and Value factors demonstrated resilience, particularly in long-short portfolios.

Keywords: Factor Investing, European Corporate Bond Market, ESG, Momentum, Value, Low-Risk, Size, COVID-19 Crisis.

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Section 1: Introduction

The growing focus on Environmental, Social, and Governance (ESG) factors in investment strategies is underscored by the substantial growth of assets allocated to ESG Exchange-Traded Funds (ETFs), going from 5 billion U.S. dollars in 2006 to 403 billion U.S. dollars as of November 2022 (Statista, 2023). According to Statista Research Department (2023), this growth has been primarily driven by developed markets, mainly Europe. Despite this growing interest in ESG within equity markets, its role in the bond markets still needs to be explored. This gap is particularly noteworthy given the size and importance of bond markets, highlighting the need for further research in this area (Goldstein et al., 2017).

Transitioning to factor investing, which incorporates various drivers of return known as "factors," ESG considerations have recently gained prominence, as evidenced by (Cai et al., 2021), who found that the method of ESG implementation significantly impacts portfolio performance. However, the application of factor investing in the corporate bond market, particularly in Europe, is limited. This thesis aims to address this gap. The methodology employed is adapted from Houweling & Van Zundert, (2017), chosen for its comprehensive approach and robust foundation for this study. Specifically, this study extends existing research by incorporating ESG factors into traditional factor models, focusing on the European corporate bond market. It also comprehensively explains how these factors perform during the COVID-19 crisis, offering valuable insights for academic research and practical investment strategies.

Given the gaps in existing literature and the potential implications for academia and practice, this study seeks to answer a critical question. The research question is: "*How do the five factors – ESG, Size, Value, Low-Risk, and Momentum –influence returns and risk-adjusted performance in long-short and long-only portfolios in the European corporate bond market, especially during the COVID-19 crisis?*".

Given Kaiser (2020) findings on the potential for *ESG* factors to improve risk-adjusted returns, this study aims to test the following empirically:

Hypothesis 1: High ESG-rated bonds outperform low ESG-rated bonds in the European corporate bond market when integrated with the existing four-factor investing model (Size, Low-Risk, Value, and Momentum).

Finally, considering research by Engelhardt et al., (2021) and Baltussen et al. (2021), which suggested that *ESG* factors and multi-factor bond strategies could offer better risk-adjusted returns and stability during market crises, the study further hypothesizes:

Hypothesis 2: The performance of the six-factor model outperforms the benchmark across different market crises, like the COVID-19 crisis.

This research provides substantial insights into factor investing within the European corporate bond market, focusing on ESG integration among other factors. Over the whole sample period from February 2015 to May 2023, long-only portfolios generally exhibit statistically insignificant but positive alphas, whereas long-short portfolios lean towards negative alphas. Notably, the Low-Risk and Momentum factors display particularly strong performance in long-only portfolios, with alphas of 1.133% and 1.699%, respectively. During the COVID-19 crisis, captured through interaction terms, the resilience of ESG and Value factors in long-short portfolios is evident, although the long-short portfolios as a whole underperformed compared to their long-only counterparts. This divergence in performance across different portfolio constructions and market conditions necessitates further scholarly exploration.

The remainder of this thesis is organized as follows: Section 2 provides a Literature Review, Section 3 explains the Data Sources, Section 4 details the Methodology, Section 5 presents the Results, Section 6 is the Discussion, Limitations, Future studies and Robustness and Section 7 Concludes the study.

Section 2: Literature Review

The following literature review aims to provide a comprehensive overview of factor investing, particularly in the European corporate bond market context. This review is structured to explore critical factors - *Size, Low-Risk, Value, Momentum*, and *ESG* - that have been identified as significant in asset pricing models. Additionally, the review delves into the impact of market conditions, such as the COVID-19 crisis, on the corporate bond market. The objective is to establish the current state of academic understanding, identify gaps in the literature, and set the stage for the empirical analyses that will follow in this thesis. The review draws upon various scholarly articles, empirical studies, and theoretical frameworks to offer a multi-faceted perspective on the complexities and opportunities within factor investing in the European corporate bond market.

2.1 Factor Investing

Factor investing, characterized by the construction of portfolios whose risks and exposures align with well-known and persistent drivers of return known as "factors," has attracted tremendous attention in recent years. The origins of factor investing can be traced back to Sharpe's development of the Capital Asset Pricing Model (CAPM) Sharpe, (1964), followed by the introduction of multi-factor models such as the Arbitrage Pricing Theory (APT) (Merton, 1974).

Although primarily utilized within equities, exploring well-established factors such as Low-Risk, Value, Size, and Momentum, its application to the corporate bond market is more recent and circumscribed (Houweling & Van Zundert, 2017).

In the corporate bond realm, factor investing pertains to portfolio construction based on specific bond characteristics: Size*, Low-Risk, Value, and Momentum*. Bonds of small companies (based on the market value of their outstanding bonds) constitute size portfolios. *Low-risk* portfolios contain bonds with high credit ratings and short maturities, while *Value* portfolios select bonds whose credit spreads exceed their model-implied fair spread. Lastly, momentum portfolios consist of bonds that have demonstrated high past returns. Single-factor and multi-factor portfolios have generated statistically significant alphas that bear economic importance (Houweling & Van Zundert, 2017).

Investments in the European corporate bond market, marked by considerable fragmentation, particularly during financial crises, leverage factor investing for alpha generation. The technique has proven robust to various sensitivity analyses, considering alternative factor definitions and portfolio construction methods (Houweling & Van Zundert, 2017). The rapid growth of factor investing, with investments between USD 1-2 trillion worldwide in intelligent beta, quant, and factor-based strategies, highlights its significance in the finance industry (Baltussen et al., 2021).

Baltussen et al. (2019) explored factor premiums in global bond markets over a 221-year sample period. They found that bond factors, notably *Value, Momentum, and Low-Risk*, yielded attractive, consistently high-performing premiums, even during rising yield periods. Huij et al. (2014) emphasized that investors must assess the pros and cons of both long-only and long-short approaches for factor investing, as the apparent superior risk-adjusted performance of a simple long-short method might involve considerable limitations.

2.2 European corporate bond market and COVID-19 crisis

The European corporate bond market, a key funding source for Eurozone corporations, demonstrates intricate dynamics and diversity. Periods of financial stress, such as the 2008-2009 global financial crisis and the 2011-2012 Eurozone sovereign crisis, unveiled marked market fragmentation. Disparities appeared in corporate bond yields across Eurozone countries, even for bonds with identical credit ratings and maturities (Horny et al., 2018).

However, unconventional monetary policy implementations, such as the Outright Monetary Transaction (OMT) and quantitative easing, substantially alleviated this fragmentation (Zaghini, 2017)—this understanding of market dynamics, including financial effects. Crises and policy responses support applying factor investing in the European corporate bond market.

The COVID-19 crisis unleashed a significant liquidity crisis on the corporate bond market, marked by increased transaction costs, a shift to liquid securities, and inverted trade-size pricing. Dealers, particularly non-primary ones, switched from buying to selling, leading to a dramatic drop in inventories, most noticeable in the two weeks before Federal Reserve System interventions. High-cost liquidity provisions surged in electronic customer-to-customer trading. The Federal Reserve's actions, including the Primary Dealer Credit Facility and the Secondary Market Corporate Credit Facility, played a vital role in stabilizing trading conditions. The bulk of the bond liquidity impact materialized after the announcement of these facilities, reflecting a newly assumed role of the Federal Reserve as a market maker of last resort (O'Hara & Zhou, 2021).

In the European corporate bond market, COVID-19 spurred fragmentation and liquidity challenges. However, Federal Reserve interventions helped stabilize the global market. At the same time, the European Central Bank's implementation of the Pandemic Emergency Purchasing Programme (PEPP) acted as a stabilizing force against systemic risks. This intervention had a notable impact on significant market participants, such as large banking institutions and non-banking financial intermediaries like investment funds, which saw substantial capital outflows, particularly from assets with low liquidity (Falato et al., 2021; Ma et al., 2022).

The liquidity crisis revealed disorderly markets, lacking a market maker with the financial resources and knowledge to buy and sell prices confidently. The demonstrated solution was for the central bank to assume the role of market maker of last resort, either by purchasing assets directly or facilitating such purchases by accepting these assets as collateral. This approach effectively resolved the liquidity issues plaguing the corporate bond market (O'Hara & Zhou, 2021).

2.3 ESG

The impact of Environmental, Social, and Governance (*ESG*) factors on firm value has primarily been explored from the perspective of the stock market, with relatively few studies investigating this relationship from the perspective of the corporate bond market. Sharfman & Fernando, (2008) examines the relationship between improved environmental risk management and a firm's cost of capital. Their study of 267 U.S. firms found that better environmental risk management was associated with a lower cost of capital. Their study suggested that firms benefit from enhanced environmental risk management through reductions in their cost of equity capital, a transition from equity to debt financing, and increased tax benefits from the ability to add debt. This study added a new dimension to the discussion on the environmental-economic performance relationship, which had previously focused predominantly on improvements in economic performance resulting from better resource utilization.

ESG factors have emerged as a significant consideration for investors, particularly in Europe. As regulation, societal expectations, and recognition of climate risks intensify, a strong *ESG* profile is increasingly linked to better financial performance and lower risk levels (Friede et al., 2015).

On the other hand, a study conducted by Menz, (2010) examined the relationship between corporate social responsibility (CSR) and the valuation of Euro corporate bonds and reported a weak positive relationship. Interestingly, the study found that ceteris paribus, the risk premium for socially responsible firms – classified by the SAM Group – was higher than for non-socially responsible companies. However, this relationship was marginally significant in only one of the models investigated. This suggested that incorporating CSR into corporate bond pricing is ongoing. These findings underscore the complexity of the relationship between *ESG* factors and bond market performance and the necessity of further research in this area.

Recent literature provided new perspectives on the *ESG*-bond performance relationship. Gehricke et al. (2023) indicated that the *ESG*-return relationship could become positive as investors increasingly acknowledge *ESG*-related risks and opportunities. Their research suggested that investing in bonds from firms with high *ESG* performance did not inherently lead to under or overperformance, especially in sectors like energy where bond returns post the Paris Agreement demonstrated a positive correlation with *ESG* factors. This was consistent even when *ESG* ratings from multiple providers were considered, reinforcing the robustness of their findings despite the divergence in ratings across different providers.

2.4 Size

The concept of the *Size* effect, predominantly defined as the phenomena where smaller firms outperform larger ones, measured by higher risk-adjusted returns, was first introduced by (Banz, 1981). Banz, (1981) expanded on the Capital Asset Pricing Model (CAPM) by introducing an additional *Size* factor, calculated as the market value of an asset minus the average market value, divided by the average market value. Despite lacking a solid theoretical foundation, Banz's findings indicated the existence of this effect, particularly within the smallest companies in the sample.

Subsequently, Fama & French, (1993) advanced this notion by proposing a three-factor model, an extension of the original CAPM. This model incorporated the *Size* effect to capture the outperformance of small firms relative to larger ones. They operationalized the *Size* factor by calculating the differential returns of small stocks minus big stocks (SMB), using the market capitalization as the proxy for size. Despite the broad application of the Fama-French three-factor model, it is noteworthy that this representation of the *Size* effect is not universally accepted.

Banz, (1981) suggested that smaller firms may be more illiquid, vulnerable to financial distress, and potentially susceptible to losses under changing market conditions, thereby potentially yielding higher returns. Further behavioral justifications for the size premium have been provided by Stambaugh et al., (2012), who posited that mispricing might occur due to limited investor attention towards smaller companies. In this regard, Fama & French, (1992) corroborated the existence of a size premium in small-cap stocks.

The *Size* factor's effect has been predominantly explored in the equity market. Still, its application in the bond market and its impact on corporate bonds remain an area of ongoing research. Studies by (Bektić et al., 2019) applying the Fama-French five-factor model to the bond market found that the *Size* factor had a minimal impact and did not generate significant excess returns. This study contradicts the findings in the equity market, suggesting possible market segmentation in the factors influencing returns across different markets.

However, an alternative perspective on the *Size* factor within the bond market was proposed by (Houweling & Van Zundert, 2017). Instead of relying on the equity market value, they measured size using the total index weights for each issuing company. They found that the *Size* portfolio generated a significant excess return for investment- and non-investment-grade bonds.

2.5 Value

The notion of the *Value* factor finds its roots in the works of Fama & French, (1996), who recognized that *Value* stocks, those stocks that have a lower price compared to their fundamental value, consistently outperformed growth stocks in a majority of the main markets from 1975 to 1995. This observation formed a *Value* strategy consisting of buying underpriced stocks and selling overpriced ones, with the price determined relative to their fundamental value, often denoted by the book-to-market ratio.

Before Fama and French's landmark study, Basu, (1977) critically evaluated the efficient market hypothesis, proposing that low P/E ratio securities tend to outperform high P/E ratio securities, a phenomenon that the efficient market hypothesis could not fully account for. His conclusion questioned the blanket applicability of the efficient market hypothesis in explaining diverse risk-adjusted returns.

Value strategies were not only limited to equity markets. L'Hoir & Boulhabel, (2010) extended these strategies to corporate bond portfolio construction, utilizing a "signal combination" method that used valuation, equity return, and earnings momentum as markers. This approach yielded consistent, positive risk-adjusted returns, underlining the effectiveness of diversification in enhancing portfolio performance.

The relation between a firm's value and its likelihood of bankruptcy also emerged as a critical research area. As observed by Correia et al., (2012), changes in credit spreads were strong predictors of changes in a firm's probability of default, thus affecting its value.

Fama & French, (1996) further validated the concept of the value factor by identifying a consistent pattern where value stocks outperformed growth stocks across diverse markets. Their findings were robust irrespective of the definition of the value proxy, be it book-to-market, price/earnings, cash flow/price, or dividend/price ratios.

Graham, (1985) advocated for the investment in underpriced stocks, assuming that these stocks have the potential to generate higher returns. This perspective was later incorporated into Fama & French, (1992) model, where they defined underpriced stocks as those with a high book-to-market ratio.

Applying the *Value* factor to the credit market, L'Hoir & Boulhabel, (2010) identified underpriced bonds based on the deviation of real credit spread from the theoretical value. M. Correia et al., (2012) took a multi-faceted approach by considering profitability, volatility, and the distance-to-default measure.

Despite the *Value* factor's prominence in equity markets, its relevance in corporate bonds is more complex. Bektić et al., (2019) suggested that the equity value risk premium does not significantly influence corporate bonds. This finding supports prior research that implied the *Value* factor may not fully apply to fixed-income markets due to structural equity-bond relations (Merton, 1974). Hence, using the *Value* factor on equities and bonds provides insight into market segmentation and emphasizes the unique attributes of the corporate bond market.

2.6 Low-Risk

The concept of *Low-Risk* investment strategies has been illuminated by a multitude of studies, suggesting that meticulously curated *Low-Risk* portfolios can challenge the conventional belief that riskier assets invariably offer superior returns in recompense for the accompanying higher risk (Baker & Haugen, 2012 ; Haugen & Heins, 1972). These studies provide comprehensive evidence supporting the *Low-Risk* anomaly. Low-risk assets consistently yield superior risk-adjusted returns compared to their high-risk counterparts across various markets and time frames.

Theoretical justifications for the *Low-Risk* anomaly largely hinge upon behavioral finance explanations, asserting that investors often overestimate the rewards of high-payoff assets, inflating their prices and consequently depressing their returns (Barberis & Huang, 2008). The reverse scenario is observed for lower-risk assets, often underpriced due to lesser demand, providing opportunities for superior returns. Institutional factors, such as leverage and short-selling constraints, also elucidate this anomaly (Frazzini & Pedersen, 2014).

In the fixed-income sector, scholarly investigations demonstrate that bonds exhibiting lower risk levels tend to outperform (Ilmanen et al., 2004). Distinctive metrics, such as credit ratings and time to maturity, are the foundation for assessing risk within this context. Interestingly, portfolios of higher-rated, leveraged bonds can outperform those of lower-rated, de-leveraged bonds (Frazzini & Pedersen, 2014).

Moreover, academic discourse has constructed "defensive portfolios" to represent the *Low-Risk* factor, using variables such as market leverage, effective duration, and profitability to evaluate the issuer's risk level (Israel et al., 2015). Research indicates that high-rating, short-maturity bonds can be safer than their low-rating, long-maturity counterparts (Houweling & Van Zundert, 2017).

Delving further into this anomaly, Bektić, (2018) has shed light on the low beta anomaly's significance in the under-researched arena of corporate bond markets. His study showcased that bonds issued by firms exhibiting a low equity beta could deliver higher risk-adjusted returns, offering a potentially lucrative strategy for corporate bond investors. This relationship between risk and recovery appears to be less steep than the CAPM would suggest and, at times, even negative, offering compelling evidence for the low beta anomaly in corporate bond markets.

This line of research underscores the potential value of incorporating low-beta strategies in an investment portfolio, with findings revealing that bonds with a low equity beta consistently produce significant risk-adjusted returns, bolstering the Sharpe ratio by up to 30%. It is worth noting that these returns hold substantial even after accounting for transaction costs (Bektić, 2018).

In conclusion, empirical evidence across equity and bond markets suggests the prevalence and profitability of *Low-Risk* strategies. While the mechanisms driving this phenomenon are multi-faceted and involve behavioral, institutional, and informational factors, the *Low-Risk* anomaly offers intriguing possibilities for investors seeking to enhance their portfolio's risk-return profile.

2.7 Momentum

The concept of *Momentum*, or *Momentum* investing, is a well-explored topic in financial literature and plays a significant role in predicting future returns. Jegadeesh & Titman, (1993) were pioneers in this research area, revealing that buying high-performing securities while selling poor performers could yield significant positive returns over short to mid-term periods. The returns generated from such a strategy are primarily due to behavioral factors rather than systematic risk or market frictions (Jegadeesh & Titman, 1993). The authors also found that returns generated from *Momentum* investing were generally persistent during the first 12 months post-formation but reduced by approximately half after more extended holding periods.

Pospisil & Zhang, (2010) and Jostova et al., (2013) extended this research into the corporate bond market, documenting the existence of momentum profits. Differentiating between investment grade and high-yield bonds, it was found that *Momentum* strategy returns primarily came from the long side – buying winners – rather than shorting losers. Interestingly, this diverges from the equity momentum scenario, where the momentum profitability mainly arises from the short side of the transaction. Jostova et al., (2013) discovered that the momentum strategy was only profitable in high-yield bonds, not in investment-grade bonds.

In recent years, more sophisticated understandings of momentum investing have emerged. Barth et al., (2017) explored momentum trading within the European corporate bond market. Their findings echoed earlier studies, identifying bond momentum among noninvestment grade bonds, which yielded up to 1% per month even after risk adjustments. They proposed that the delayed diffusion of firm-specific news could be a potential source of momentum.

This idea was further explored by Lin et al., (2020), who found a significant momentum effect across the corporate bond universe, with the effect more pronounced for lower-grade bonds and those with an embedded call option. Their research suggested that the momentum effect was short-term, weakening considerably after one year and disappearing after two years. The authors concluded neither liquidity nor conventional risk factors could explain the significant risk-adjusted momentum returns in the corporate bond market.

2.8 Multi-Factor Portfolios

While not a novel one, the concept of multi-factor investing has drawn significant attention due to its potency in capturing multiple risk dimensions, thus deviating from the traditional market risk explained by the Capital Asset Pricing Model (CAPM). Since the advent of indexing in the 1960s and 1970s, there has been a paradigm shift in the perception of risk and returns. Despite its efficiency in considerable diversification, low fees, buy and hold strategy, and low turnover, the once predominant single-factor model has been criticized for treating all risks uniformly, which fails to reflect the multifaceted realities of the market (Bender et al., 2013).

Multi-factor investing postulates that different risks reward investors differently, offering potentially superior returns than the traditional CAPM model while still adhering to the tenets of indexing. Diversification across multiple factors reduces the risk associated with single-factor portfolios, such as the underperformance of small-cap companies relative to their large-cap counterparts or past winners failing to outperform past losers (Bender et al., 2013).

Adding another dimension to the discussion, factor index-based investing can be considered active decision-making manifested through passive replication. Traditionally, institutional investors' asset allocation centered around two key return sources: Beta and Alpha. The former refers to the return from broad market exposure, which can be achieved by investing passively in a market-tracking portfolio. The latter symbolizes the additional return active management can generate over the market capitalization-weighted index. Multi-factor investing presents a novel approach to exposure to systematic factors that were traditionally attainable only through active management (Bender et al., 2013).

In implementing multi-factor portfolios, it is essential to consider the interplay of factors. Research by Baltussen et al., (2021) brought to light the potential of combining various bond factors - *Value, Momentum, and Low-Risk* - into a single multi-factor portfolio. The study demonstrated that such a portfolio configuration yielded significant risk-adjusted returns, outperforming a passive government bond portfolio.

It is worth noting that implementing multi-factor portfolios should be tailored to the specific investor's risk tolerance, investment objectives, and market outlook. Baltussen et al., (2019) found that different factors perform differently under various market conditions, so a strategic combination of factors can help maximize returns while minimizing risk. The diversification benefits of multi-factor portfolios could be enhanced by strategically selecting and combining less or negatively correlated factors. As the study suggested, this approach can create a multi-factor portfolio that delivers significant risk-adjusted returns while providing a buffer against diverse market conditions.

Section 3: Data

The data was gathered from Eikon Refinitiv, a reputable open-technology platform widely used by financial markets professionals, offering industry-leading data, insights, and exclusive news. With a global reach across 180+ countries and collaboration with over 30,000 firms, Eikon Refinitiv provides trusted content and analytics, making it a reliable source for comprehensive financial data.

The data was sourced from the Eikon Refinitiv add-on in Microsoft Excel. Specifically, the list of constituents for the Stoxx 600 was retrieved as of December 31, 2022. Subsequently, all bonds issued by these constituent companies between February 2015 and May 2023 were extracted for analysis.

The following information was retrieved from Eikon Refinitiv: Spread over the benchmark, Modified duration, market value capital, and Total return index. All these variables from Eikon Refinitiv are measured monthly. To use as risk-free, I got the monthly "Euro yields - 5 years" and "Euro yields - 10 years" from February 2015 to May 2023 from the Eurostat website.

The final dataset is comprised of 2,982 bonds issued by 232 different issuers. Roughly, all the bonds are investment grade, and only a handful, around 0.3% of the sample, belong to high yield. This was expected since the sample is from bonds issued by companies in the Stoxx 600.

A short description of the variables is below.

1. **Bond Identifier (ISIN)**: A unique code identifying a specific bond issue.
2. **Issuer Name**: The name of the company that issued the bond.
3. **Issue Date**: The date when the bond was issued. The date is presented in the format DD/MM/YYYY.
4. **Maturity Date**: The date when the bond's principal amount becomes due and payable. The date is presented in the format DD/MM/YYYY.
5. **Credit Rating**: A credit rating agency assigns a rating reflecting the issuer's creditworthiness. I have collected credit ratings from Moody's and Fitch. The ratings go from AAA (highest) to BB (lowest).
6. **ESG Rating**: A score assigned by a rating agency, in this case, MSCI(Morgan Stanley Capital International), that assesses a company's performance in

environmental, social, and governance factors. This is a numerical variable from 0 to 100, 100 being the best.

7. **Total Return Index (RI)**: It signifies the total return on an investment, considering both the bond's interest payments and price changes. It is calculated using the formula:

$$RI= \frac{(P + A - (Pt{-}1 + At{-}1) + CP)}{(Pt{-}1 + At{-}1)}$$

   Where RI is Total Return, P is Clean Price, A is Accrued Interest, and NC is Next Coupon. An adjustment is made when a bond goes ex-dividend, CP is the Value of any coupon received on t, or since t – 1, t is Time, and t -1 is Time less one day.

8. **Spread Over Benchmark (SP):** This term refers to the difference in the yield of a bond and the equivalent government benchmark bond for the bond's currency of denomination, expressed in basis points. This yield difference is calculated using the bond's maturity and yield and often uses linear interpolation for maturities that do not precisely match those of available government benchmark bonds.
9. **Modified Duration:** This measures the interest rate sensitivity of a bond. It calculates the expected percentage change in the bond price for a 1% change in interest rates. It is a weighted average of the times until a bond's fixed cash flows are received and indicates a bond's volatility in response to changes in interest rates.
10. **Market Value Capital (MV):** This represents the current market value of a bond issue. It is calculated by multiplying the bond's current market price by the amount in euros currently in the problem. This gives an indication of the bond's worth on the market at any given point in time.

The monthly return of a bond can be calculated simply by the division of RI at time t and RI at time t-1, minus one:

$$Monthly\ Return\ t= \frac{\mathrm{RI\ t}}{\mathrm{RI\ t-1}}$$

Excess return is calculated by subtracting the average of the 5-year Euro yield curve and 10-year Euro yield curve from the bond's total return. These measures were chosen as a risk-free rate because they closely match the maturity (8.29 years).

Table 3.1 shows the summary statistics for the dataset that were collected. The annualized excess return is the monthly return of the debt security minus the return of Treasuries with the same duration. Time to maturity indicates the number of years until the bond reaches maturity. Credit spread is the Spread Over the Benchmark. The market value of a company indicates the sum of the market values of all bonds of an issuer. The number of observations is the average amount of bonds per month in the sample. For every variable, the mean and five significative percentiles are reported (5%, 25%, 50%, 75% and 95%).

Table 3.1 Summary Statistics of Dataset, February 2015 - May 2023

	Mean	5%	25%	50%	75%	95%
Monthly excess return (%)	-0.001%	-3.708%	-0.675%	0.079%	0.799%	3.232%
Time to maturity (years)	8.29	1.883	3.682	5.208	7.217	53.963
ESG	80.974	65.9747	74.1888	80.3393	89.281	93.648
Credit spread (bps)	139.336	38.800	79.000	115.400	171.800	311.400
The market value of aggregated bonds (millions €)	20.616	1.119	4.833	13.974	33.285	58.125

Average bond-month observations	1383

Source: own calculations with data from Eikon Refinitiv

Section 4: Methodology

This section presents the definition of the five factors ESG: Size, Low-risk, Value and Momentum, portfolio construction and regressions, and performance metrics that are used. The influential paper significantly informs this factor analysis (Houweling & Van Zundert, 2017). Their innovative approach and methodology provide an essential framework for my analysis. However, this study diverges by concentrating on the European corporate bond market and utilizes distinct variables acquired from Eikon Refinitiv.

4.1 ESG Factor

The Environmental, Social, and Governance (*ESG*) factor plays a significant role in this thesis. The *ESG* factor is computed using the combined ESG Score provided by Refinitiv®, a leading global provider of financial market data.

Refinitiv® ESG Scores are a comprehensive measure of a company's resilience to long-term, financially relevant ESG risks. The scores are designed to measure the relative ESG performance of a company transparently and objectively across ten key categories that span three pillars: Environmental (E), Social (S), and Governance (G). These categories include Resource Use, Emissions, and Innovation for the Environmental pillar; Workforce, Human Rights, Community, and Product Responsibility for the Social pillar; and Management, Shareholders, and CSR Strategy for the Governance pillar.

The ESG Combined Score is calculated based on aggregating the scores from the three pillars (E, S, and G), comprehensively evaluating a company's overall ESG performance. An essential aspect of the ESG Combined Score is its consideration of ESG controversies. If a company is involved in an ESG controversy, it is penalized, which affects its overall ESG Combined Score. The event's impact can persist into the following year if new developments related to the adverse event, such as lawsuits, ongoing legislation disputes, or fines.

In the present analysis, the *ESG* factor is used to sort bonds. The idea is to understand the role of *ESG* factors in bond performance. A high ESG score could indicate lower risk and better performance, and vice versa. By comparing the performance of bonds with high and low ESG scores, the study aims to uncover the potential impact of *ESG* factors on bond returns.

4.2 Size factor

The *Size* factor will be estimated using the “market_value_capital” variable, representing the current month's market value of a bond issue. To calculate the total market value for each company, I will aggregate the “market_value_capital” of all bonds issued by the same company in my dataset. This approach allows me to estimate the total amount issued by each company accurately.

In constructing my portfolios, I sort bonds based on this aggregated “market_value_capital.” Bonds from companies with higher total market values are deemed larger and form the Size portfolio.

In the context of corporate bonds, it is noteworthy to mention that smaller companies typically issue smaller bonds. Since smaller bonds often display lower liquidity levels than larger ones, as shown by Sarig & Warga, (1989), my definition of Size incorporates a potential illiquidity premium. In essence, the Size factor captures the size of the issuing company and indirectly reflects the bonds' liquidity, providing a more detailed understanding of the risk-return trade-off.

4.3 Value Factor

The principle of *Value* investing, initially introduced in the equity markets by Basu, (1977), can also be applied to the corporate bond market. This principle suggests mean-reversion in valuations, indicating that undervalued securities tend to outperform overvalued ones over time.

To operationalize this concept in the bond market, I compare the market's required compensation for the bond's risk, as represented by the Spread from Benchmark Curve (SP), to fundamental risk measures. A bond is deemed 'cheap” if it offers an ample reward for the risk investors bear.

The Spread from the Benchmark Curve is the difference in yield between the bond and a duration-matched government benchmark bond for the bond’s denomination currency. The spread is expressed in basis points and obtained through linear interpolation.

Following the approach proposed by L’Hoir & Boulhabel, (2010) and M. Correia et al., (2012), I adapt three risk measures from the bond market data: the bond's SP (Spread from Benchmark Curve), its rating, and the three-month change in the bond's SP. The inclusion of the three-month change in SP is informed by the findings of Norden & Weber,

(2004) and Norden, (2017), who demonstrate that yields tend to increase three months before a rating downgrade, serving as a worthwhile risk indicator.

To construct the *Value* factor portfolios each month, I execute a cross-sectional regression with the following specifications:

$$SP\_i = \alpha + \sum \beta\_r * I\_ir + \gamma * Time\_to\_maturity\_i + \delta * \Delta SP\_i + \varepsilon\_i$$

Where SP_i is the Spread from the Benchmark Curve of bond I, I_ir equals 1 if bond i has rating r, and 0 otherwise, Time_to_maturity_i is the time to maturity of bond I, and ΔSP_i is the three-month change in SP of bond i.

Following the estimation of the above regression, I compute the percentage difference between the actual SP and the fitted SP for each bond. I then rank the bonds based on this percentage difference from high to low. The top 10% of bonds (with the highest percentage difference) comprise the top *Value* portfolio, while the bottom 10% (with the lowest percentage difference) form the bottom *Value* portfolio.

I can systematically identify and invest in undervalued bonds by utilizing this methodology, creating a bond investment strategy based on the *Value* factor.

4.4 Low-Risk Factor

The creation of the *Low-Risk* factor was guided by a rigorous two-step process previously done by Ilmanen, (2011), developed to minimize both credit and interest rate risks inherent in the bond market. This process incorporated two primary bond characteristics: credit ratings and time to maturity.

The initial step was centered around credit risk. To this end, bonds were ordered from the highest to the lowest credit rating each month. Credit ratings, a standardized measure of a bond's creditworthiness, provided insight into the bond issuer's financial health and ability to fulfill their financial commitments. In this step, all bonds rated AAA were selected. This selection process effectively shortlisted those bonds that exhibited superior creditworthiness.

The subsequent step concentrated on mitigating interest rate risk. The shortlisted bonds from the initial step were ordered from shortest to longest time to maturity. Time to maturity, as an indicator of a bond's sensitivity to changes in yield, represents the bond's exposure to interest rate risk. From these bonds, all bonds shorter than a certain maturity threshold M years were selected each month such that the portfolio made up 10% of the total number of bonds. Notably, the maturity threshold M was dynamic and fluctuated over time, accommodating varying market conditions.

The resulting *Low-Risk* top portfolio, therefore, consisted of bonds that had high credit ratings and a short time to maturities, indicating minimal exposure to credit and interest rate risks these will be the high ones. This methodology ensured that the Low-Risk factor captured the selection of bonds that were most insulated from the two main types of bond risk.

For the *Low-Risk* bottom portfolio, the process was slightly different. All bonds rated below AAA were selected. The longest 10% of the bonds were selected each month from these bonds. These bonds represent the ones with lower credit ratings and longer time to maturity.

In conclusion, this systematic and objective approach to portfolio construction ensures that the *Low-Risk* factor encapsulates the selection of robustly secure bonds from the two principal aspects of bond risk.

4.5 Momentum Factor

The *Momentum* factor will be calculated using the excess return calculated with the average of the monthly 10-year Euro Yield curve and monthly 5-year Euro yield curve, which closely matches the average duration of my bond dataset (8.29 years). This excess return is the difference between the bond's total return and the return on the 10-year Euro yield curve and 5-year Euro yield curve. This alignment ensures consistency in my assessment. The 10-year Euro yield curve and 5-year Euro yield curve data are obtained from the Eurostat website.

The *Momentum* is the past six-month return, excluding the most recent month, to avoid short-term reversals. This implementation follows the model proposed by (Jostova et al., 2013). To calculate this, I first measure the six-month return for each bond using a one-month lag. Then, the bonds are ranked based on these past returns.

The top 10% of bonds with the highest past returns are selected to form the top *Momentum* portfolio, signifying positive momentum. Conversely, the bottom 10% with the lowest past returns constitute the bottom *Momentum* portfolio, representing negative momentum. This methodological approach effectively identifies and tracks momentum trends within the corporate bond market.

4.6 Portfolio Formation

The research methodology for this study centers on the formation of single-factor and multi-factor portfolios of corporate bonds, sorted based on their exposure to each of the five identified factors: *ESG, Size, Low-Risk, Value, and Momentum*.

For each factor, monthly, equally weighted portfolios of the top and bottom 10% of bonds, determined by their factor exposure, are constructed. This selection percentage can be adjusted based on specific research requirements and risk tolerance.

Two types of single-factor portfolios are created:

1. **Long-Short Single-Factor Portfolios**: These portfolios incorporate long and short positions. The top 10% of scoring bonds form the long positions, while the bottom 10% of the lowest-scoring bonds constitute the short positions.
2. **Long-Only Single-Factor Portfolios**: These portfolios are constructed by taking a long position in the top decile (10%) of securities as ranked by a specific factor every month. Notably, these portfolios abstain from incorporating any short positions.

In addition to the single-factor portfolios, a **Long-Only Multi-Factor Portfolio** is developed to analyze the combined influence of all five factors. This portfolio is created by assigning equal weighting (20% for each factor in this study) to each single-factor portfolio, selecting the top 10% of bonds. All these portfolios are examined over a one-month investment horizon.

Table 4.1 and Table 4.2 present key descriptive statistics for the excess return distribution of long and long-short portfolios across various factors. The returns are calculated every month and are not annualized. The statistics include measures of central tendency, dispersion, and higher moments - namely skewness and kurtosis - to provide a comprehensive view of the distributional characteristics of each factor's returns.

Table 4.1. Descriptive statistics for Long-Only portfolios' excess returns over duration-matched treasuries

	L_ESG	L_Size	L_LowRisk	L_Value	L_Momentum	Multi_factor
Mean	0,17%	0,17%	0,22%	0,10%	0,27%	0,19%
volatility	1,40%	1,45%	1,43%	1,46%	1,71%	1,39%
Max	3,41%	3,47%	3,86%	3,12%	4,35%	2,52%
Min	-6,57%	-6,67%	-7,95%	-7,64%	-9,96%	-7,66%
Skewness	-1,290	-1,365	-2,083	-1,652	-1,920	-1,998
Kurtosis	4,903	4,824	10,729	7,372	12,431	9,342

Table 4.2. Descriptive statistics for Long-short portfolios' excess returns over duration-matched treasuries

	LS_ESG	LS_Size	LS_LowRisk	LS_Value	LS_Momentum	Market
Mean	0,07%	0,04%	0,10%	-0,04%	0,07%	0,15%
volatility	0,74%	0,45%	0,82%	0,55%	2,39%	1,46%
Max	3,51%	1,62%	2,68%	2,36%	5,73%	3,34%
Min	-2,13%	-2,31%	-2,23%	-1,78%	-9,50%	- 6,81%
Skewness	1,031	-1,108	0,475	0,404	-1,104	-1,402
Kurtosis	5,207	8,199	1,503	4,197	4,267	4,985

Table 4.1 focuses on long-only portfolios. All factors, on average, show positive excess returns, with the *Momentum* portfolio leading at 0.27%. Volatility levels are relatively consistent across the portfolios, ranging from 1.39% to 1.71%. Skewness values are negative for all portfolios, indicating a distribution with a longer left tail. Notably, the Low-Risk and Momentum portfolios exhibit exceptionally high kurtosis values of 10.729 and 12.431, respectively, suggesting "fat-tailed" distributions.

Table 4.2 provides insights into long-short portfolios. Mean returns vary widely, with the *Low-Risk* portfolio showing a positive mean of 0.10% and the *ESG* and *Value* portfolios displaying negative means. All mean returns are lower than the market mean return. Volatility is generally lower than in long-only portfolios, except for the *Momentum* portfolio, which has the highest volatility at 2.39%. Skewness is predominantly negative, except for the *Low-Risk* portfolio, which has a positive skewness of 0.475. Kurtosis varies substantially, with the *ESG* portfolio indicating a 'fat-tailed' distribution with a kurtosis of 10.224.

Compared to Table 4.1, where long-only portfolios are considered, the long-short portfolios in Table 4.2 generally exhibit lower mean returns and volatilities, except for the Momentum portfolio, which has a lower return but higher volatility.

Table 4.3 Mean monthly return for all portfolios deciles portfolios' excess returns over duration-matched treasuries

Deciles	ESG	Size	LowRisk	Value	Momentum	Multi_factor
1	0,10%	0,13%	0,12%	0,14%	0,21%	0,14%
2	0,13%	0,15%	0,19%	0,11%	-0,14%	0,16%
3	0,14%	0,13%	0,13%	0,03%	0,01%	0,13%
4	0,19%	0,11%	0,20%	0,09%	0,02%	0,09%
5	0,12%	0,12%	0,14%	0,03%	0,10%	0,09%
6	0,13%	0,18%	0,13%	0,04%	0,16%	0,10%
7	0,11%	0,11%	0,15%	-0,05%	0,23%	0,09%
8	0,19%	0,15%	0,13%	-0,12%	0,31%	0,10%
9	0,01%	0,00%	0,13%	0,02%	0,39%	0,08%
10	0,17%	0,17%	0,22%	0,10%	0,27%	0,19%

In Table 4.3, the mean monthly returns for various factors across deciles are displayed. Ideally, one would expect higher returns in higher deciles. However, the data shows some deviations from this pattern. For example, the *Value* factor has negative returns in certain deciles, and the *Momentum* factor shows an irregular pattern. These inconsistencies suggest that the relationship between deciles and returns may not be straightforward and could require further study to fully understand.

Figure 4.1 presents the time series of cumulative monthly excess returns for portfolios long on each factor from February 2015 to May 2023. An impressive upward trajectory is evident among all factors, registering notable cumulative returns over the sample period. *Momentum* is the leading investment strategy, delivering a substantial cumulative return of 27.23%. This is followed closely by *Low-Risk* with a return of 22.03%. The Multi-Factor portfolio also shows a strong performance, achieving a cumulative return of 18.59%. *Size* and *ESG* have generated 17.08% and 16.60% returns, respectively, while Value lags with a 10.22% return. All these factors, except value, have outperformed the market's excess return of 14.51%.

It is imperative to underscore that these results do not incorporate transaction costs or portfolio turnover. This omission is particularly impactful for strategies like *Momentum*, which necessitate frequent portfolio rebalancing, potentially altering the feasibility and profitability of the strategy.

Figure 4.1. Cumulative monthly excess return for long portfolios on each factor, February 2015 – May 2023

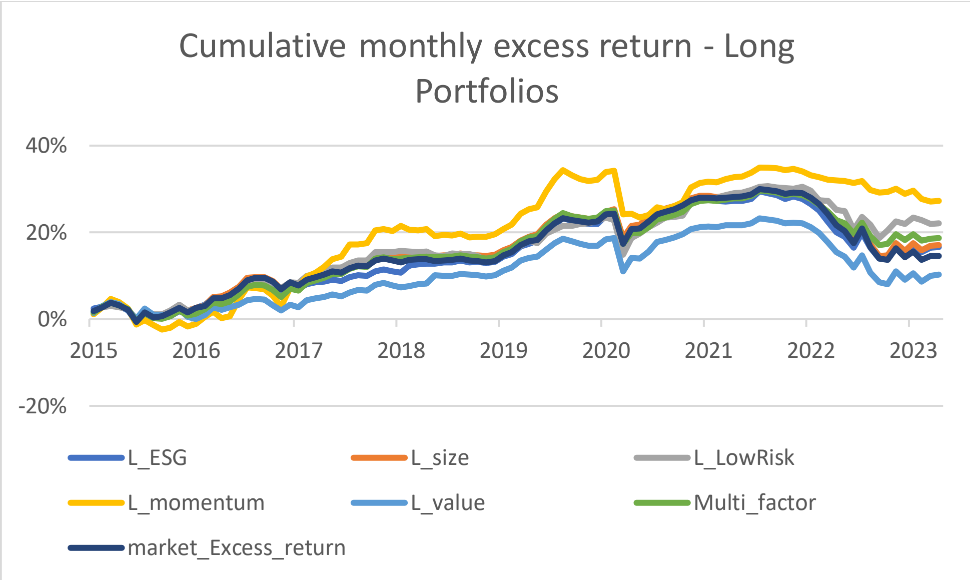

Figure 4.2 *Cumulative monthly excess return for long-short portfolios on each factor, February 2015 – May 2023*

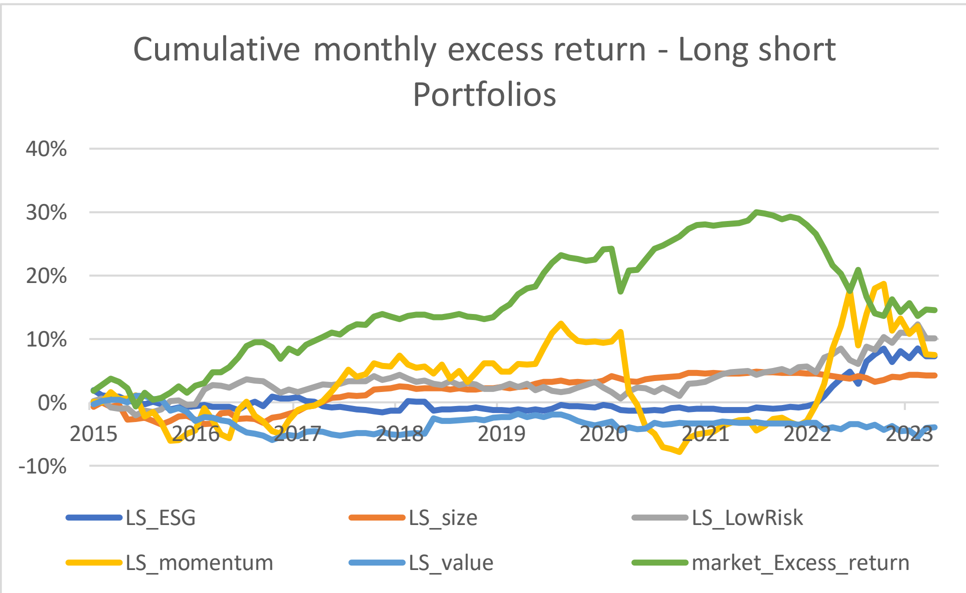

Figure 4.2 delineates the cumulative monthly excess returns for long-short portfolios across various factors, covering the period from February 2015 to May 2023. The Long-short portfolio data reveals disappointing outcomes, significantly since none of the factors outperformed the market's excess return of 14.51%. The *Low-Risk* long-short portfolio emerges as the standout performer, yielding a cumulative return of 10.10%, followed closely by the ESG, Momentum and *Size* portfolios with returns of 7.23%,7.47% and 4.28% and respectively. On the other end of the spectrum, the *Value* portfolio could not achieve positive returns, registering negative returns of -3.94%.

The COVID-19 pandemic caused an unparalleled market condition with far-reaching effects on the European corporate bond market. Among these effects was a considerable shift in the behavior of the *Momentum* factor. Cicchiello et al., (2022) reported a significant widening of credit spreads during the pandemic, particularly in the green bond sector, indicating an elevated level of risk perceived by investors. Interestingly, the study found that the announcement of vaccine effectiveness led to a sudden reversal in these credit spreads. This phenomenon could explain the significant fluctuations observed in the returns of the LS_momentum portfolio during 2020.

4.7 Regressions

The outperformances and alphas of factor portfolios were calculated versus the market segment. Two primary models were used to estimate these metrics: the Capital Asset Pricing Model (CAPM) and a six-factor model.

The Capital Asset Pricing Model (CAPM), pioneered by Sharpe, (1964) and Lintner, (1965), serves as a fundamental tool in this study's analytical framework. As a single-factor model, the CAPM elucidates a portfolio's returns through the lens of the market's excess return. The alpha derived from the CAPM, in essence, represents the portion of the portfolio's return that remains unexplained by the market's return, thereby providing a measure of the portfolio's outperformance against the market.

Complementing the CAPM, this study also employs a six-factor model, which extends the CAPM by incorporating additional factors to provide a more comprehensive explanation of a portfolio's returns. These factors typically encompass *Size, Value, and Momentum*, among others identified as significant in elucidating returns.

The CAPM model is expressed as follows:

$$Rt=\alpha+\beta \mathrm{DEF}t+\varepsilon t,$$

Where Rt is the return on a factor portfolio, and DEFt represents the corporate bond market premium. The intercept of this regression is the CAPM-alpha.

The modified six-factor model, adapted for my study, is represented by:

$$Rt=\alpha+\beta 1\mathrm{ESGt}+\beta 2\mathrm{SIZt}+\beta 3\mathrm{LRt}+\beta 4\mathrm{VALt}+\beta 5\mathrm{MOMt}+\beta 6\mathrm{DEFt}+\varepsilon t,$$

Where ESGt is the ESG rating, SIZt is the Size factor, LRt is the Low-Risk factor, VALt is the Value factor, MOMt is the Momentum factor, and DEFt is the corporate bond market premium, which is calculated by the market premium of the benchmark minus the risk-free rate.

4.8 Outperformance Metrics

The following metrics were used for performance: the Sharpe and Sortino Ratio.

The Sharpe ratio, developed by Nobel laureate William F. Sharpe, is widely used in finance for assessing the performance of investments, considering both return and risk. The Sharpe ratio measures the excess return (or risk premium) per unit of deviation in an investment asset or a trading strategy, typically called risk (Sharpe, 1966).

The formula is as follows:

$$Sharpe\ Ratio=\frac{\mathrm{Rp}-\mathrm{Rf}}{\sigma \mathrm{p}}.$$

The Sortino ratio, developed by Frank A. Sortino, modifies the Sharpe ratio by differentiating harmful volatility from total overall volatility using the asset's standard deviation of negative portfolio returns, called downside deviation. The Sortino ratio is helpful for investors, analysts, and portfolio managers to evaluate an investment's return for a given level of bad risk (Sortino & Price, 1994).

Like the Sharpe Ratio, the Sortino Ratio is a risk-adjusted performance measure. However, the Sortino Ratio only considers downside risk, making it more useful for investors who want to account for potential losses in their risk estimation. It can be calculated as follows:

$$Sortino\ Ratio = \frac{\mathrm{Rp - Rf}}{\mathrm{Downside\ Deviation}},$$

Where Rp is the portfolio return, Rf is the risk-free rate, and Downside Deviation is the standard deviation of the negative asset returns.

Furthermore, I will investigate the performance of the six-factor model during the COVID-19 crisis and compare it to the benchmark performance.

The COVID-19 crisis presents a unique period for analyzing factor investing in the European corporate bond market. The pandemic has exerted unprecedented pressure on global financial markets, including the European corporate bond market. This period is characterized by high volatility and uncertainty, providing a rich context for studying the resilience and performance of different investment strategies.

In their study, Capelle-Blancard et al., (2021) examined the performance of socially responsible (SR) investment strategies during the COVID-19 crisis. They found that, on average, SR indexes exhibited dynamics similar to their conventional benchmarks. However, there was substantial heterogeneity in the financial performance of SR strategies, with impact strategies slightly outperforming their benchmarks. Furthermore, the resilience of SR strategies was more robust in countries and during periods in which the number of COVID-19 cases was increasing.

These findings suggest that the COVID-19 crisis period provides a valuable context for studying the performance of different investment strategies, including factor investing in the European corporate bond market. The unique market conditions during this period can offer insights into the resilience and performance of these strategies under extreme market stress.

For this thesis, the COVID-19 crisis period was defined as the first half of 2020, which includes both the fever period (February 24–March 20) and the rebound period (March 23–May 29), meaning the months of February, March, April and May will be analyzed. This period aligns with the timeline used by Capelle-Blancard et al., (2021) and captures the initial shock of the pandemic and the subsequent market response. A dummy variable was created to flag this crisis period, and interaction terms were introduced in the regression models to capture the factor-specific effects during this time.

Section 5: Results

The following section presents a detailed analysis of my findings concerning long-short and long-only single-factor portfolios within the European corporate bond market. I will explore the implications of different factor allocations, *ESG, Size, Value, Low-Risk, Momentum, and* the multi-factor portfolio. The results are derived from the regression statistics for CAPM and the 5-factor Fama-French models, covering the period from February 2015 to May 2023.

A one-tailed Student's t-test determines statistical significance with 98 degrees of freedom, chosen explicitly as my null hypothesis is directional, aiming to test whether the factors' alpha is greater than zero. The assumption of heteroskedasticity and autocorrelation, common phenomena in financial time-series data and mainly observed in our alpha correlations, has been addressed using Newey-West standard errors. This robust method corrects for these biases in the error term, enhancing the reliability of the statistical inferences. Applying Newey-West standard errors also adjusts the t-values, providing a more robust measure for hypothesis testing in heteroskedasticity and autocorrelation. Significance levels are denoted as follows: * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level. All values are annualized.

5.1 Long-Short Factor Portfolios

Table 5.1. OLS *Regression statistics for CAPM, Six-factor model, and correlations of long-short portfolios. February 2015 – May 2023*

	ESG	*Size*	*Value*	*Low-Risk*	*Momentum*
Panel A. CAPM statistics					
Alpha	-0,285%	0,378%	-0,612%	1,241%	2,351%
t-Value	0,323	0,755	1,021	1,321	0,881
Beta	0,090	0,078	0,080	-0,017	-0,836
$R^{2\,a}$	0,040	0,065	0,045	0,001	0,263
R^2_{adjusted}	0,030	0,055	0,035	0,009	0,255
Panel B. 6 Factor model statistics					
Alpha	-0,544%	0,258%	0,374%	-0,006%	-0,484%
t-Value	0,744	0,648	1,458	0,009	0,548
$R^{2\,a}$	0,266	0,233	0,854	0,716	0,914
$R^2_{\text{adjusted}}{}^a$	0,219	0,184	0,844	0,698	0,909
Panel C. CAPM alpha correlations					
ESG	1,000				
Size	0,071	1,000			
Value	-0,029	0,073	1,000		
Low-Risk	0,261	-0,058	-0,040	1,000	
Momentum	0,019	-0,067	-0,431	-0,201	1,000
Panel D. Outperformance statistics					
Outperformance	-1,869%	-1,227%	-2,214%	-0,529%	-0,845%
Sharpe ratio	-0,055	0,332	-0,248	0,427	0,108
Sortino ratio	-0,063	0,372	-0,349	0,761	0,121

Note: n=100. T-values are based on Newey-West standard errors. R^2 and adjusted R^2 values are omitted from the table due to the presence of multicollinearity, as indicated by high VIF values for specific predictors. The study focuses on more robust statistical measures such as alpha, t-values, and Newey-West standard errors to assess model fit and significance. All figures are annualized. [a]Multicollinearity present, which might lead to the overestimation of R^2 values.

Source: own calculations with data from Eikon Refinitiv, *replication of Table 2 of Houweling and van Zundert (2017) with added Outperformance statistics (panel D) and R^2 values.*

In Table 5.1, the results for the long-short factor portfolios are shown. In the context of the CAPM model, none of the alphas are statistically significant at conventional levels, with low t-values. The *Low-Risk* factor, however, posts a positive alpha of 1.241%, and the *Momentum* factor shows a comparatively higher alpha of 2.351%, albeit still statistically insignificant. The R^2 and $R^2_{adjusted}$ values are notably low, ranging from 0.001 to 0.263, implying limited explanatory power.

Turning to the Six-Factor Model, all factors continue to be insignificant, with the Value factor leading with an alpha of 0.374%. Conversely, the *ESG* and *Momentum* factors display alphas of -0.554% and-0.484%, respectively, remaining statistically insignificant. The R^2 and $R^2_{adjusted}$ values show an inflated pattern, with the *Momentum* factor reaching as high as 0.914. This inflation is likely due to multicollinearity, as substantiated by elevated VIF values in the regression diagnostics.

The alpha correlations under CAPM reveal intricate relationships among factors. A noteworthy observation is the negative correlation between *Momentum* and *Value* (-0.431), suggesting potential diversification benefits. On the other hand, a positive correlation exists between *Low-Risk* and *ESG* (0.261), hinting at a complementary relationship.

Regarding risk-adjusted returns, panel D shows that the Sharpe ratios vary across factors, with the *Low-Risk* factor leading at 0.427 and ESG lagging at -0.055. The Sortino ratios further corroborate these observations, with *Low-Risk* again at the forefront with 0.761 and *ESG* at the rear with -0.063.

In conclusion, Table 5.1 offers an enriched understanding of the dynamics at play within the European corporate bond market, especially the complexities introduced by multicollinearity. Despite these challenges, the *Momentum* factor stands out for its return in CAPM, and the correlations between factors offer insights into potential diversification strategies.

5.2 Long-Only Portfolios

Table 5.2. OLS *Regression statistics for CAPM, six-factor model, and correlations of long portfolios. February 2015 – May 2023*

	ESG	*Size*	*Value*	*Low Risk*	*Momentum*	*Multi-factor*
Panel A. CAPM statistics						
Alpha	0,365%	0,346%	-0,438%	1,133%	1,699%	0,621%
t-Value	1,020	1,465	0,821	1,415	1,096	1,380
Beta	0,935	0,979	0,956	0,867	0,901	0,928
R^2	0,959	0,978	0,916	0,783	0,595	0,952
$R^2_{adjusted}$	0,959	0,978	0,915	0,781	0,591	0,952
Panel B. 6 factor model statistics						
Alpha	0,409%	0,241%	-0,729%	0,898%	1,330%	
t-Value	1,212	1,061	1,280	1,212	0,789	
R^{2a}	0,966	0,983	0,923	0,804	0,614	
$R^2_{adjusted}$[a]	0,964	0,982	0,919	0,794	0,593	
Panel C. CAPM alpha correlations						
ESG	1,000					
Size	-0,103	1,000				
Value	0,137	0,247	1,000			
Low Risk	-0,182	0,172	0,031	1,000		
Momentum	-0,098	0,122	0,059	0,188	1,000	
Multi-factor	0,049	0,353	0,388	0,572	0,812	1,000
Panel D. Outperformance statistics						
Outperformance	0,252%	0,309%	- 0,514%	0,902%	1,526%	0,490%
Sharpe ratio	0,412	0,409	0,242	0,532	0,552	0,463
Sortino ratio	0,458	0,434	0,262	0,513	0,570	0,462

Note: n=100. T-values are based on Newey-West standard errors. R^2 and adjusted R^2 values are omitted from the table due to the presence of multicollinearity, as indicated by high VIF values for specific predictors. The study focuses on more robust statistical measures such as alpha, t-values, and Newey-West standard errors to assess model fit and significance. [a]Multicollinearity present, which might lead to the overestimation of R^2 values.

Source: own calculations with data from Eikon Refinitiv, *replication of Table 3 of Houweling and van Zundert (2017) with added Outperformance statistics (panel D) and R^2 values.*

Expanding upon the insights from long-short portfolios, Table 5.2 thoroughly examines long-only factor portfolios in the European corporate bond market from February 2015 to May 2023. The factors under scrutiny remain *ESG, Size, Value, Low-Risk, Momentum, and* a Multi-factor portfolio.

In the context of the CAPM model, all factors, except for Value with an alpha of -0.438%, exhibit positive alphas. The *Momentum* factor stands out with an alpha of 1.699%. However, it is worth noting that these alphas are not statistically significant, as indicated by their respective t-values. The R^2 values range from 0.595 for *Momentum* to 0.978 for *Size*, suggesting a robust model fit. However, these values are likely inflated due to multicollinearity, as corroborated by high VIF values.

Transitioning to the Six-Factor Model, the narrative remains mostly the same. All alphas, except for ESG, are relatively lower than the CAPM and still insignificant. Also, the *Momentum* factor still leads with an alpha of 1,330%. The R^2 and adjusted $R^2_{adjusted}$ values continue to be exceptionally high, with the multi-factor portfolio even achieving a perfect fit, necessitating caution due to multicollinearity.

The alpha correlations among the long-only portfolios are less intense than their long-short counterparts but still noteworthy. For instance, a strong correlation of 0.812 between the Multi-factor and *Momentum* portfolios suggests significant alignment. Furthermore, the *Size* and *ESG* factors show a negative correlation of -0,103 and a *Low-Risk* and *ESG of* -0,182, which shows potential diversification benefits.

Focusing on risk-adjusted metrics, the *Momentum* factor continues to excel with a Sharpe ratio of 0.552 and a Sortino ratio of 0.570. The *Low-Risk* factor also shows promise with a Sharpe ratio of 0.532 and a Sortino ratio of 0.513. Outperformance metrics are mixed but generally positive, with *Momentum* leading at 1.526% and Value lagging at -0.514%.

In summary, Table 5.2 enriches our understanding of long-only factor portfolios, complementing the preceding analysis on long-short portfolios. While the alphas are mainly positive compared to the long-short portfolios, their statistical insignificance complicates the interpretation of portfolio performance. The elevated R^2 and adjusted R^2 values, although indicative of a good model fit, are likely skewed upwards due to multicollinearity. The *Momentum* factor remains robust in risk-adjusted terms, but the diversification potential is less promising in the long-only space due to higher correlations. This multifaceted analysis provides a comprehensive view of factor dynamics in the European corporate bond market and underscores the necessity for meticulous model selection and portfolio strategy.

5.3 COVID-19 crisis analysis

The COVID-19 crisis in the first half of 2020 presented a unique set of challenges and opportunities for factor investing in the European corporate bond market. This thesis focuses on the period from February to May. This timeline captures both the initial market shock and subsequent recovery, according to (Capelle-Blancard et al., 2021).

During the COVID-19 crisis, systemic risks and liquidity constraints redefined the market landscape. O'Hara & Zhou, (2021) noted a spike in transaction costs and a shift towards liquid securities, impacting factors like *Momentum*. Regulatory interventions, notably the Federal Reserve's Primary Dealer Credit Facility and the Secondary Market Corporate Credit Facility, served as liquidity backstops. Concurrently, the European Central Bank's Pandemic Emergency Purchasing Programme (PEPP) helped stabilize systemic risks. These measures significantly influenced key market players, including large banks and non-bank intermediaries like investment funds, which experienced substantial outflows, especially from illiquid assets ((Falato et al., 2021); (Ma et al., 2022)).

In this volatile context, I anticipate notable fluctuations in the performance of factor-based portfolios. This tumultuous period, marked by regulatory interventions and shifts in liquidity, provides a complex backdrop for our empirical analysis of factor investing during the COVID-19 crisis.

Table 5.3 Interaction Effects on Excess Returns of Long-Short Portfolios During the COVID-19 Period

	LS_ESG	*LS_Size*	*LS_Value*	*LS_Low Risk*	*LS_Momentum*
CAPM coefficient	8.679**	1.674	4.797***	2.915**	-0.309
Six Factor Coefficient	-0.117	-0.584***	-0.093	0.268***	-0.032

Note: n=4. T-values are based on Newey-West standard errors.

Table 5.4 Interaction Effects on Excess Returns of Long-Only Portfolios During the COVID-19 Period

	L_ESG	*L_Size*	*L_Value*	*L_Low Risk*	*L_Momentum*	*Multifactor*
CAPM coefficient	0.021	0.055**	-0.046	-0.054	0.123	-0.143**
Six Factor Coefficient	-0.019	-0.017	-0.011	0.005	-0.040	

Note: n=4. T-values are based on Newey-West standard errors.

The empirical results in Tables 5.3 and 5.4 illuminate the intricate dynamics of factor premiums during the COVID-19 period. Using the CAPM and a Six-Factor Model, the analysis quantifies the interaction effects of five factors—ESG, size, value, low-risk, and momentum—on excess returns.

Starting with Table 5.3, the ESG factor in Long-Short portfolios stands out with a significant CAPM coefficient of 8.679 significant at the 5% level, signifying a strong factor premium during the pandemic. Similarly, the Value factor shows a significant coefficient of 4.797 significant at the 1% level under CAPM, indicating robust premiums.

Turning to the Momentum factor, it was negative, but it did not show significance, which could be attributed to liquidity conditions during the pandemic, as described by O'Hara & Zhou (2021).

When we expand our lens to include additional risk factors through the Six-Factor Model, the narrative changes, for instance, the previously robust Value factor becomes insignificant with a coefficient of -0.093, questioning its stability during this period. The Size factor undergoes a dramatic shift, flipping from a positive CAPM coefficient of 1.674 to a significantly negative -0.584 significant at the 1% level, suggesting smaller firms were hit harder.

In contrast, Table 5.4, focusing on Long-Only portfolios, shows a different landscape with coefficients lower when compared to the Long-short portfolios. The Size factor remains relatively stable when transitioning from CAPM to the Six-Factor Model, moving from a significant coefficient of 0.055 significant at the 5% level to an insignificant -0.017, implying these portfolios are less sensitive to the inclusion of extra risk factors.

Section 6: Discussion, Limitations, and Future Research

The study aims to address its research question and hypotheses in this section, drawing upon the empirical findings presented in earlier sections on factor performance in both long-short and long-only portfolios, emphasizing the COVID-19 crisis. Although the research question is broad and does not lend itself to a singular answer, insights can be inferred from the analyses. Additionally, this section will delineate the study's limitations and outline avenues for future research.

6.1 Hypothesis

Hypothesis 1: High ESG-rated bonds will outperform low ESG-rated bonds when integrated with a four-factor investing model (Size, Low-Risk, Value, and Momentum).

The results of this study present a contradicting picture regarding the performance of ESG-rated bonds when integrated with other factors. For the entire period, the alpha for ESG in long-short portfolios was -0.544% under the Six-Factor Model, corroborating earlier findings by Kaiser, (2020) that suggest no significant incremental return for high ESG ratings. On the other hand, the long-only portfolios under the Six-Factor Model exhibited an alpha of 0.409%, although statistically insignificant, indicating a more positive but still inconclusive relationship.

During the COVID-19 crisis, the Six-Factor Model yielded an insignificant coefficient of -0.117 for the ESG factor in long-short portfolios. Similarly, in long-only portfolios, the coefficient was also insignificant at -0.019. These results deviate from the findings presented by Engelhardt et al., (2021), who suggested that European firms with elevated ESG ratings performed better during the COVID-19 crisis. On the other hand, if we look at the CAPM while ignoring the integration of the ESG factor into the model, we see that the long-short ESG portfolio has a significant coefficient of 8.679 during the COVID-19 crisis.

Hypothesis 2: The six-factor model will outperform the benchmark across different market crises, such as the COVID-19 crisis.

During the COVID-19 crisis, the Six-Factor Model yielded mixed results. In long-short portfolios, the *Size* and *Low-Risk* factors showed significantly negative and positive coefficients of -0.584 statistically significant at the 1% level, and 0.268 statistically significant at the 1% level, respectively. These findings are in line with Baltussen et al., (2021), who indicate the resilience of the *Low-Risk* factor across various market conditions, including crises. However, the *ESG* factor produced an insignificant coefficient of -0.117.

Overall, the Six-Factor Model produced varied outcomes depending on the period and portfolio construction, showing a more stable picture in the entire sample period.

6.2 Factor Performance in Long-Short and Long-Only Portfolios

While the performance of factors in the European corporate bond market is a subject of ongoing research, understanding their behavior in different portfolio constructions - long-short and long-only - provides valuable insights into their robustness and applicability.

Specifically, all portfolios, long-only and long-short, presented non-significant alphas, with the alphas for the long-short portfolios being lower than the long-only portfolios. This contrasts with the findings of Houweling & Van Zundert, (2017) and Dekker et al., (2019), who reported significant alphas in corporate bonds. The discrepancy may be attributed to the unique market conditions of the European Corporate Bond and the period analyzed or the inclusion of additional factors such as *ESG*.

Focusing on long-only portfolios, these display generally positive but statistically insignificant alphas. The *Momentum* factor showed a high but statistically insignificant alpha in the CAPM model, aligning with Jegadeesh & Titman, (1993) and finding resonance in the work of (Baltussen et al., 2021). This suggests that factor premiums may be more robust in long-only portfolios across different asset classes. On the other hand, Value showed a negative return both in the CAPM and in the six-factor model, which goes against the findings of (Houweling & Van Zundert, 2017).

In summary, our analysis yields differentiated outcomes. Long-short portfolios exhibit insignificant alphas, diverging from prior literature and potentially reflecting the influence of unique market conditions for the European corporate bond market or additional factors like *ESG*. Long-only portfolios generally show positive and higher alphas than long-short portfolios, but they are statistically insignificant, with *Momentum* standing out in risk-adjusted terms. Notably, the *Low-Risk* factor displayed overall positive alphas in both long-only and long-short portfolios, corroborating the “low beta anomaly” found by Bektić (2018) and extending its applicability beyond equity markets.

6.3 Crisis Period Analysis

Transitioning to the crisis period analysis, we focus on the performance of various factors, particularly their resilience or vulnerability during turbulent market conditions.

The *ESG* and *Size* factors in the six-factor model displayed remarkable resilience during the crisis. In the context of the COVID-19 crisis, the Six-Factor Model produced mixed results. Although the *ESG* factor yielded a negative but statistically insignificant coefficient of -0.117 in the Six-Factor Model, I has a positive coefficient of 8.679 significant at the 1% level in the CAPM context, which supports the findings of Alessandrini et al., (2021) who reported that ESG-tilted portfolios contribute to modifying exposure to credit risk.

Moving on to the Size factor, it showed resilience by yielding positive coefficients in both the long-short and long-only portfolios under the CAPM framework. However, it turned negative and significant under the Six-Factor Model. This shift casts doubt on the robustness of the *Size* factor in explaining returns across different model specifications, a point that refutes the country-specific findings of Pandey et al., (2021), who discovered that the *Size* factor is an important determinant of returns in Spain and Italy. It is worth noting, however, that their study was country-specific, and the implications may differ in a broader European context.

Contrastingly, the *Momentum* factor experienced a decline, turning insignificant in both long-short and long-only portfolios, having only a small positive coefficient in the long-only portfolio in CAPM. This aligns with Barth et al., (2017), who found *Momentum* to be predominantly present during expansions and exclusive to non-investment grade bonds.

The coefficients were generally positive for most factors during the crisis. This corroborates with traditional market behavior, which usually sees a flight to quality or more established factors during crises. Dekker et al., (2019) and Henke et al., (2019) provide support, emphasizing that factors like Value yield excess returns in different markets.

In summary, the COVID-19 crisis period analysis highlights that factors such as *ESG* and *Size* demonstrate resilience in certain contexts, while *Momentum* appears notably vulnerable. This divergence in factor performance during crisis periods underscores the need for further research to understand how these factors can be effectively incorporated into investment strategies during market volatility.

6.4 Limitations and Future Research

In pursuing an understanding of factor investing in the European corporate bond market, this study encounters several limitations that warrant careful consideration. These limitations can be broadly categorized into data-related and methodological constraints. On the data front, the study grapples with a limited sample size sourced from Eikon Refinitiv. Methodologically, the study faces challenges related to the omission of transaction costs and liquidity constraints and the fact that the dataset was retrieved from the Stoxx 600 on 31/12/2022. Each limitation impacts the interpretability and generalizability of the findings and offers avenues for future research to enhance the robustness and applicability of the insights generated.

One significant concern in this study stems from the constrained data access in Eikon Refinitiv. From the Stoxx 600 issuers, only approximately 220 had available information. This limited sample size may introduce biases, such as autocorrelation, that constrain the statistical power of the analysis and overshadow subtleties that a more extensive dataset could reveal. Future studies might consider utilizing other data sources, thereby enhancing the generalizability of the findings.

In this study, the omission of transaction costs and liquidity constraints could limit the real-world applicability of the findings, as these factors can significantly impact portfolio performance. Houweling & Van Zundert, (2017) offer a methodological approach to address this by calculating break-even transaction costs, which would lower a portfolio's CAPM-alpha to zero. This is achieved by determining portfolio turnover and dividing the portfolio's gross alpha by this turnover. The paper also considers liquidity by focusing on the most liquid bonds, providing a multifaceted perspective. Their findings suggest that portfolios can still generate positive after-cost alphas, highlighting the importance of incorporating these factors in future research.

It is crucial to address the issue of survivorship bias introduced by the data collection methodology. Specifically, the study employed issuers from the Stoxx 600 as of December 2022 to examine a period ranging from 2015 to 2023. This approach inadvertently excludes issuers that were part of the Stoxx 600 at any point during the study period but were no longer listed as of December 2022. As a result, the analysis may overestimate asset performance by focusing solely on "survivors," thereby introducing a bias that could affect the generalizability of the findings. The more appropriate methodology would have been to include all issuers that were part of the Stoxx 600 at any time within the 2015-2023 timeframe, tracking their performance throughout the period irrespective of their subsequent inclusion or exclusion from the index. This would have provided a more comprehensive and unbiased view of asset returns in the European corporate bond market.

Policymakers might also consider these findings when evaluating the systemic risks of factor-based investment strategies. The data constraints limitations and other limitations further suggest that these stakeholders should seek additional corroborative studies before substantially changing investment or regulatory frameworks.

By clearly delineating these limitations, the study acknowledges the constraints and areas for potential improvement. The suggestions embedded within each limitation also provide a roadmap for future research, aiming to enhance the depth and applicability of the insights generated within the context of European corporate bond factor investing. The limitations underline the necessity for meticulousness in the data collection process and the methodological approach, emphasizing the multifaceted nature of factor investing in the European corporate bond market.

6.5 Robustness results

The robustness checks in this study include an analysis of long-only portfolios using both deciles and quintiles. The decile-based analysis (Table 5.2) reveals that the *Low-Risk* and *Momentum* factors exhibit the highest alphas in the CAPM model, while the *Value* factor shows a negative alpha. In contrast, the quintile-based analysis (Table 10.1) indicates a notably high alpha for the *Momentum* factor, especially in the six-factor model, where it is statistically significant at the 5% level. Interestingly, the alpha for *Value* remains negative in both decile and quintile analyses, suggesting consistent underperformance.

The correlation matrices presented in the decile and quintile analyses offer insightful observations into the interrelationships among various factors. Notably, the *Multi-factor* portfolio exhibits enhanced correlations with each of the individual factors when analyzed through quintiles rather than deciles. This heightened correlation suggests that the quintile framework may provide a more robust representation of the multifactorial influences on returns. Furthermore, the correlation between the *ESG* and *Low-Risk* factors also shows a marked increase when transitioning from the decile to the quintile model, underscoring the potential for the quintile approach to capture more nuanced relationships among the factors.

Lastly, the outperformance statistics show that *Momentum* has the highest Sharpe and Sortino ratios in the quintile analysis, indicating superior risk-adjusted returns. This contrasts with the decile analysis, where *Low-Risk* and *Momentum* are more closely matched. These variations between decile and quintile analyses offer valuable insights into the sensitivity of factor performance to portfolio construction methods.

Section 7: Conclusion

In addressing the central research question, *"How do the five factors – ESG, Size, Value, Low-Risk, and Momentum –influence returns and risk-adjusted performance in long-short and long-only portfolios in the European corporate bond market, especially during the COVID-19 crisis?"*, this study has traversed a complex landscape of factor dynamics, statistical models, and market conditions. The findings, encapsulated in Tables 5.1 through 5.4, offer a multifaceted understanding of factor investing in the European corporate bond market. While the CAPM model yielded mixed results for alphas in long-short portfolios, the *Low-Risk* and *Momentum* factors stood out, with alphas of 1.241% and 2.351%, respectively. Notably, the study revealed complex inter-factor relationships, such as the slight negative correlation between *Momentum* and *Value*, providing opportunities for diversification.

Utilizing both long-short and long-only portfolios, this research offers an understanding of factor performance. In long-short portfolios, the *Momentum* factor showed a positive but statistically insignificant alpha under the CAPM model. However, the *Momentum* factor's coefficient was negative, -0.309 during the COVID-19 crisis, highlighting its vulnerability to market volatility. In long-only portfolios, the *Momentum* and *Low-Risk* factors had the highest alphas with 1.699% and 1.133%, respectively, under the CAPM model.

The study's limitations, particularly the constrained data access, underscore the need for methodological rigor in future research. Moreover, the omission of transaction costs and liquidity constraints in the current study highlights an area for future inquiry, as these factors can significantly impact real-world portfolio performance.

The COVID-19 crisis acted as a real-world stress test for factor performance, uncovering vulnerabilities in the Momentum factor, as evidenced by its negative coefficient of -0.309 in long-short portfolios. Conversely, the crisis revealed resilience in the *ESG* and *Value* factors, with the *ESG* factor showing a CAPM coefficient of 8.679 significant at the 5% level and the Value factor at 4.797 significant at the 1% level in long-short portfolios. These findings underscore the importance of a dynamic investment strategy that can adapt to market exigencies, particularly during periods of extreme volatility. In light of the pronounced market shifts during the COVID-19 crisis, future research in this area would do well to incorporate these fluctuations to create a more robust framework for factor investing in volatile markets.

The relevance of this research lies in its focus on the European corporate bond market, a less-explored area in literature. Moreover, including the *ESG* factor adds a contemporary layer to the study. At the same time, examining the COVID-19 crisis period offers a unique perspective on factor performance under market stress. Therefore, this study addresses its research question and contributes to the broader discourse on factor investing.

In conclusion, this study contributes to the existing literature by thoroughly examining factor investing in the European corporate bond market. While the study's limitations provide a roadmap for future research, its findings suggest immediate insights for investors, portfolio managers, and policymakers. Therefore, this study advances academic understanding and has practical implications for the broader financial community. This study underscores the complexity and potential of factor investing in the European corporate bond market in a rapidly evolving economic landscape. It serves as a foundation for future research and a guide for practitioners, emphasizing the need for adaptability and methodological rigor in academic inquiry and investment strategy.

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Appendix

Table 10.1 *Regression statistics for CAPM, six factor model and correlations of long portfolios using quintiles. February 2015 – May 2023*

	ESG	*Size*	*Value*	*Low Risk*	*Momentum*	*Multi-factor*
Panel A. CAPM statistics						
Alpha	0,485%	0,342%	-0,420%	0,485%	2,463%	0,671%
t-Value						
Beta	0,908	0,976	0,955	0,946	0,946	0,938
R^2	0,947	0,980	0,916	0,956	0,839	0,977
$R^2_{adjusted}$	0,946	0,980	0,915	0,956	0,838	0,977
Panel B. 6 factor model statistics						
Alpha	0,486%	0,176%	-0,797%	-0,012%	2,174%**	0,000%
t-Value	1,102	0,890	1,218	-0,037	2,327	1,430
R^{2a}	0,958	0,985	0,928	0,964	0,858	1,000
$R^2_{adjusted}$ [a]	0,956	0,984	0,924	0,962	0,850	1,000
Panel C. CAPM alpha correlations						
ESG	1,000					
Size	-0,093	1,000				
Value	0,148	0,319	1,000			
Low Risk	0,296	0,167	0,069	1,000		
Momentum	-0,002	0,280	0,113	0,229	1,000	
Multi-factor	0,421	0,493	0,587	0,553	0,703	
Panel D. Outperformance statistics						
Outperformance	0,324%	0,300%	-0,498%	0,391%	2,295%	0,562%
Sharpe ratio	0,437	0,408	0,246	0,435	0,807	0,479
Sortino ratio	0,465	0,428	0,450	0,876	0,265	0,499

Note: n=100. t-values are based on Newey-West standard errors. R^2 and adjusted R^2 values are omitted from the table due to the presence of multicollinearity, as indicated by high VIF values for certain predictors. The study focuses on more robust statistical measures such as alpha, t-

values, and Newey-West standard errors to assess model fit and significance. [a]*Multicollinearity present which might lead to the overestimation of* R^2 *values.*

Source: own calculations, replication of Table 2 of Houweling and van Zundert (2017).