The Effect of ESG Risk Factors on the Investment Process

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The Effect of ESG Risk Factors on the Investment Process

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Summary

This research investigates the impact of Environmental, Social, and Governance (ESG) risk factors on investment processes, with a particular focus on their influence on financial performance. Despite the transition to a data-driven world, quantitative research on the impact of ESG risk factors remains insufficient in both academia and industry. This thesis addresses this gap by exploring the question: How do ESG risk factors affect the risk and return dynamics of equity investment portfolios?

The literature review presents existing research on ESG investments, providing an overview of empirical evidence regarding the financial performance of ESG-compliant investments. It explores ongoing debates about ESG ratings and their influence on stock performance, emphasizing the need for more accurate evaluation methods of ESG risks.

The methodology section outlines a comprehensive approach for assessing the impact of ESG risk factors, including data collection and preprocessing steps to ensure data accuracy and consistency. The analysis employs Principal Component Analysis to identify key ESG factors and Fama-MacBeth regression to quantify their material impact on financial performance. An extended Fama-French model is developed to integrate ESG factors into asset pricing models, offering a novel approach to understanding their influence on asset returns.

The results section provides an in-depth analysis of the performance of various financial models including the Capital Asset Pricing Model, the Fama-French 3-Factor Model and models incorporating ESG factors. The effectiveness of these models in predicting portfolio performance is assessed using metrics such as alpha distribution and beta coefficients. The construction and evaluation of different portfolios, including top-bottom and Treynor-Black weighted portfolios, reveal that ESG risk factors reduce the negative impact on investment returns.

The research emphasizes the significance of integrating ESG risk factors into investment strategies to enhance portfolio performance and manage risks effectively. However, limitations are acknowledged, including inconsistent data quality and the constraints of multi-factor models. Despite these challenges, the study contributes to understanding ESG integration in investment strategies and highlights areas for future research. These include developing more precise models that better capture the diverse impacts of ESG risk factors on financial performance and exploring the long-term effects of ESG investments across varying market conditions.

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Nomenclature

Abbreviations

Abbreviation	Definition
ESG	Environmental, Social, and Governance
SFDR	Sustainable Finance Disclosure Regulation
CSRD	Corporate Sustainability Reporting Directive
UN-PRI	United Nations Principles for Responsible Investment
SRI	Socially Responsible Investing
SASB	Sustainability Accounting Standards Board
PCA	Principal Component Analysis
CAPM	Capital Asset Pricing Model
FF3	Fama-French Three-Factor Model
FF5	Fama-French Five-Factor Model
GMB	Good Minus Bad
TNA	Total Net Assets
ROA	Return on Assets
SMB	Small Minus Big (size factor in FF3 model)
HML	High Minus Low (value factor in FF3 model)
PGGM	Pensioenfonds Zorg en Welzijn
FTSE	Financial Times Stock Exchange
IDB	Inter-American Development Bank
RF	Risk-Free Rate

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Introduction

The shift towards Environmental, Social, and Governance (ESG) investment has become a prominent trend in the asset management sector, driven by global challenges such as climate change, social inequality, and corporate governance issues. This thesis examines the growing focus on ESG investment, which aims to achieve both financial returns and measurable societal benefits (Gantchev et al., 2024; Hartzmark & Sussman, 2019). By integrating sustainability and ethical considerations into investment strategies, ESG investment is positioned as a strategic approach to fostering sustainable, forward-looking financial growth (Whelan et al., 2021). The relevance of this study extends beyond its specific application to PGGM, encompassing broader implications for the financial industry and society at large. Investigating the impact of ESG factors on investment performance addresses a pivotal question for investors and policymakers: can sustainable investing align with, or even enhance, financial returns? This question is particularly pertinent in a world confronting climate change, social inequality, and corporate governance challenges, where financial markets have the potential to drive significant positive change.

The rise of ESG investing can be traced back to the late 20th century when socially responsible investing (SRI) began gaining traction. Over time, ESG criteria have evolved and expanded, influenced by a growing awareness of global environmental issues and social responsibilities. Regulatory frameworks and policies have significantly shaped the ESG landscape. For instance, the European Union's Sustainable Finance Disclosure Regulation (SFDR) and the Paris Agreement have established guidelines and targets that drive ESG investment practices. Additionally, organizations such as the United Nations Principles for Responsible Investment (UN-PRI) have set benchmarks and principles that promote the integration of ESG factors into investment decisions. These regulations and policies not only encourage transparency and accountability but also aim to mitigate risks and ensure long-term sustainability in financial markets (Berg et al., 2023; Gantchev et al., 2024; Jacobsen et al., 2019).

1.1 Problem Definition

The rapid expansion of ESG investment has highlighted a significant challenge: the effectiveness of ESG ratings as predictors of financial performance remains uncertain and contested. Academically, ESG ratings suffer from inconsistencies due to varying methodologies across rating agencies, leading to ambiguity in their application and reliability. This inconsistency hampers the ability of researchers to draw definitive conclusions about the relationship between ESG performance and financial returns, leaving a critical gap in the literature.

From a practical standpoint, these inconsistencies pose substantial challenges for investors and asset managers who rely on ESG ratings to guide their investment decisions. The lack of standardization and the potential failure of traditional ESG ratings to capture nuanced risks—such as environmental liabilities or governance deficiencies—can lead to suboptimal investment strategies. This problem is particularly acute in scenarios where financial outcomes are tightly linked to the effective management of ESG risks.

Addressing these issues, this research proposes a shift from traditional ESG ratings to a focus on ESG risk factors. By developing a quantitative framework that incorporates ESG risk factors into asset pricing models, the study aims to provide clearer, more reliable insights into how these factors influence the risk and return dynamics of equity portfolios. This approach seeks to bridge the gap between the theoretical understanding and practical application of ESG factors in investment strategies.

1.2 Scope of Project

This project will focus exclusively on equities, which generally offer clearer insights into ESG performance due to issuers' open market disclosure obligations. By concentrating on equities, the analysis can achieve a higher degree of precision in understanding the impact of ESG factors on investment performance.

In advancing the understanding of ESG impacts, the study will adapt the quantitative impact investment framework developed by Lo and Zhang (2023) and follow the research on ESG ratings by Berg et al. (2023). A novel aspect of this project is the replacement of traditional ESG ratings with ESG risks, providing a more dynamic and comprehensive evaluation of ESG factors.

Material ESG risk factors will be rigorously analyzed to assess their potential impact on investment performance. The selection of these factors will be based on a comprehensive methodology involving correlation analysis, Principal Component Analysis, and Fama-MacBeth regression analysis. Once identified, these risk factors will be incorporated into an adjusted multi-factor model to estimate expected returns. Monthly comparative and regression analyses will then be performed to evaluate the influence of these ESG risk factors on the overall risk and return profiles of the portfolios. This methodological approach ensures a focused and in-depth examination of ESG factors within equity investments.

The data for this research will be sourced from reputable databases maintained by PGGM. ESG risk data will be obtained from Blackrock's Aladdin platform, which includes detailed daily ESG risk metrics from Sustainalytics and climate risk evaluations covering the period from January 2024 to May 2024. Daily return data for equities will be sourced from PGGM's internal database, with the FTSE World Index serving as the benchmark for overall equity performance. Additionally, factors from the Fama-French data library will be used to analyze excess returns, employing a robust and widely recognized framework for financial modeling.

By retaining the focus on equities and leveraging established quantitative frameworks while introducing the innovative approach of using ESG risks, this project aims to provide valuable insights into the financial impacts of ESG factors on equity investments. The findings will offer significant implications for both academics and practitioners, contributing to the broader discourse on sustainable finance.

1.3 Research Questions and Sub-Questions

1.3.1 Central Research Question

"How do ESG risk factors affect the risk and return dynamics of equity investment portfolios?"

To address the central research question, a comprehensive literature review is essential for understanding the current state of research on the impact of ESG factors on investment performance. This review will examine both theoretical frameworks and empirical studies to establish a solid foundation for the subsequent analysis. The research methodology is grounded in the latest advancements in quantitative analysis of ESG impacts on investments. Data collection is a crucial component of this process, involving the acquisition of ESG risk factor data from reputable sources such as Sustainalytics, MSCI, and Bloomberg. Additionally, historical financial performance data for equity portfolios—both those incorporating ESG factors and those that do not—will be gathered to facilitate a comparative analysis.

The methodology involves the application of quantitative models, specifically multi-factor asset pricing models, to incorporate ESG risk factors. Regression analysis will be employed to examine the relationship between ESG factors and portfolio performance metrics, such as excess returns over benchmarks and volatility. This analysis aids in understanding the influence of ESG risks on risk-adjusted returns. The results of these analyses will be interpreted to identify patterns and significant differences in performance attributable to ESG factors. Ultimately, conclusions will be drawn on how ESG risk factors affect the risk and return dynamics of equity portfolios, substantiated by empirical evidence.

1.3.2 Sub-Questions

Quantifying the Impact of ESG Risk Factors: *"How can the impact of ESG risk factors be quantified in a portfolio?"*

Quantifying the impact of ESG risk factors in a portfolio involves developing a financial approach that integrates these factors into traditional investment models. This can be achieved by incorporating ESG scores or ratings as additional factors in multi-factor models. Regression analysis is a key method for this quantification, as it allows for the evaluation of the relationship between ESG factors and portfolio returns and volatility. By comparing the performance of ESG-integrated portfolios with non-ESG portfolios over time, the specific impact of ESG risks can be assessed.

Using risk-adjusted performance metrics such as market premia and the Sharpe ratio helps measure the impact of ESG factors on the overall risk-return profile of different percentage ESG-ranked portfolios. These metrics provide insights into how ESG integration affects risk-adjusted returns. Regression analysis on different quantile portfolios is essential for validating the effectiveness of this approach in quantifying the impact of ESG risks. This analysis ensures that the influence of ESG factors on investment performance is reliably measured.

Evaluating Material ESG Risk Factors: *"What are the most material ESG risk factors?"*

Correlation analysis and Principal Component Analysis (PCA) are critical tools in this process. Correlation analysis helps in identifying the ESG factors that have the highest correlation with financial performance outcomes across industries. PCA reduces the dimensionality of the ESG data, highlighting the most significant factors that explain the variance in financial performance. Multicollinearity check using VIF value excluded factors are highly correlated. These statistical methods ensure that the analysis is robust and focused on the most impactful ESG factors. Documenting these findings involves compiling a list of the most material ESG risk factors for each industry, based on the analysis and stakeholder input. This list serves as a reference for investors to focus on the ESG issues that are most likely to affect financial performance.

Understanding which ESG factors are most material is the first step in addressing the central research question because it establishes which specific factors need to be considered when analyzing their impact on investment performance.

Impact of ESG Risk Factors on Portfolio Risk and Return: *"What is the relationship between ESG risk factors and the risk and return profiles of investment portfolios?"*

To explore the relationship between ESG risk factors and the risk and return profiles of investment portfolios, it is important to segment portfolios based on their level of ESG integration. This segmentation allows for a comparative analysis between portfolios with high, medium and low ESG aggregated score. Analyzing the historical performance of these segmented portfolios provides insights into their risk (volatility) and return (average returns) profiles.

Conducting a comparative study helps in assessing the differences in risk and return profiles between ESG-integrated portfolios and traditional portfolios. Statistical testing, such as t-tests and ANOVA, can be used to determine the significance of the observed differences in performance metrics. This analysis helps in understanding whether high ESG portfolios consistently show lower risk and higher risk-adjusted returns. Synthesizing the findings allows for explaining the relationship between ESG risk factors and portfolio performance, supported by statistical evidence. This explanation helps in understanding how ESG considerations influence the dynamics of investment portfolios.

1.3.3 Significance of the Study

This research contributes to the existing body of knowledge by providing empirical evidence on the financial impacts of ESG investing. The findings have significant implications for both academics and practitioners in the field of finance. Theoretically, this study advances the understanding of how ESG factors integrate with traditional asset pricing models. Practically, it offers insights for asset managers and investors seeking to align their portfolios with sustainable and ethical practices without compromising on financial performance.

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Background

This chapter provides a comprehensive background to the research presented in this thesis, focusing on the integration of Environmental, Social, and Governance (ESG) factors into investment strategies and asset pricing models. As ESG considerations increasingly influence the global financial landscape, understanding their implications for both financial performance and investment decision-making has become essential. This chapter examines the expansion of ESG investments, the ongoing debates surrounding the validity and impact of ESG ratings, and the development of advanced quantitative frameworks that incorporate ESG risks into traditional financial models. Furthermore, it explores the practical application of these concepts within the context of PGGM's 3D investment strategy, highlighting how ESG factors can be systematically integrated to enhance both financial returns and sustainable outcomes. By establishing this foundational understanding, the chapter sets the stage for the subsequent analysis and contributions of this thesis, aiming to shed light on the critical role of ESG factors in shaping contemporary investment practices.

2.1 ESG Investment Growth

The expansion of ESG investment has been significant over recent years. In 2022, global ESG assets surpassed \$30 trillion and are projected to exceed \$40 trillion by 2030, representing over 25% of the estimated \$140 trillion in assets under management (Bloomberg, 2024). This growth underscores a shifting paradigm in the financial sector, where sustainable investing is increasingly seen as a means to achieve both financial returns and societal benefits. The integration of ESG factors into investment strategies challenges the traditional perception of finance as a zero-sum game, suggesting that ethical and sustainable practices can align with profitable investment.

Investors, particularly institutional ones like pension funds, are demonstrating heightened interest in ESG investments. This trend is driven by a fiduciary duty to secure long-term value for beneficiaries, emphasizing financial returns that do not come at the expense of societal well-being. Chile's sovereign wealth and pension funds provide a notable example, showing that investments guided by ESG principles can yield comparable or even superior financial returns (Hoffmann et al., 2020). This underscores a growing recognition that sustainable practices can enhance risk management and contribute to stable, long-term performance.

Between 2017 and 2022, ESG investing attracted considerable attention, with continued strong inflows into sustainable funds, particularly in Europe, despite ongoing debates. In 2023, the performance of ESG-focused funds and exchange-traded funds (ETFs) either equaled or outperformed their traditional counterparts. Specifically, sustainable funds achieved a median return of 12.6%, compared to 8.6% for conventional funds (Ramnath, 2024). This outperformance further strengthens the argument that sustainable investing is not only a viable strategy but also a potentially superior one in terms of financial performance.

2.2 Debate on ESG Ratings

It is essential to explore how the focus on ESG integrates into broader investment strategies. The 3D investment strategy, as introduced by PGGM (2024), demonstrates this by seeking a balance between societal and financial objectives. ESG investment is evaluated both qualitatively and quantitatively to guide the allocation of capital towards companies that engage in sustainable practices, aligning investors' values with financial performance.

Commonly, ESG ratings from institutions such as Sustainalytics or the S&P serve as key measures in this evaluation. Sophisticated models are employed to assess an asset's ESG performance using specific scores or metrics like physical risk and transition risk. The academic debate continues over whether ESG ratings positively or negatively impact stock performance. Research such as that by Khan et al. (2016), which utilizes the framework from the Sustainability Accounting Standards Board (SASB), shows that firms with higher material ESG ratings often outperform. Likewise, findings by Albuquerque et al. (2019) indicate that high ESG performance is associated with lower systematic risks and higher firm value. Recent studies highlight the minimal direct relevance of ESG ratings to global stock returns, yet emphasize that associated ESG risk factors significantly influence portfolio performance (Alves et al., 2023). This underscores the importance for investors to thoroughly analyze these ratings before incorporating them into investment strategies.

ESG data provided by rating institutions may contain biases due to factors such as inconsistent rating standards, incomplete data exposure, and regional differences. This raises the question: can investors reliably use these ratings to make predictable, advantageous decisions regarding the weighting or exclusion of stocks in their portfolios? Such concerns highlight the necessity for investors to critically assess the underlying methodologies and data completeness of ESG ratings before implementing them in investment strategies. Given these challenges and debates surrounding ESG ratings, it is imperative to explore alternative approaches to evaluate the financial impacts of ESG investments more accurately.

2.3 Quantitative Framework

Recent research Alves et al. (2023) and Berg et al. (2021, 2022) on ESG influence has primarily focused on ESG ratings, but this study will use ESG risk factors to build and enhance asset pricing models based on the Lo and Zhang (2023) framework. Utilizing ESG risk rather than ratings provides a more dynamic and comprehensive approach to evaluating a company's long-term sustainability and financial performance. ESG risk factors offer a clearer picture of potential threats and opportunities that may not be fully captured by traditional ESG ratings. By integrating ESG risks into asset pricing models, investors can achieve more accurate and robust forecasts of asset returns, leading to more informed and strategic investment decisions. Furthermore, this research will test the model performance on PGGM's real portfolio performance data to evaluate the actual influence of ESG risk on the investment process. By applying the model to real-world data, the study aims to provide empirical evidence of the effectiveness of incorporating ESG risk factors. This practical evaluation will help determine whether the enhanced asset pricing model can consistently deliver better investment outcomes, offering valuable insights into the tangible benefits of ESG risk integration in portfolio management.

In assessing the financial impacts of ESG investments, Lo and Zhang (2023) built a quantitative framework based on the multi-factor model from the Fama-French model to evaluate the expected return of a stock. This framework incorporates ESG risk ratings as external factors, adjusting the expected returns of investments accordingly. ESG ratings are scores assigned by rating agencies based on a company's ESG performance, while ESG risks are specific factors related to environmental, social, and governance issues that can impact financial outcomes. The methodology involves using regression analysis to compare adjusted expectations with actual historical performance, quantifying the impact of specific ESG risks on financial outcomes. For example, Treynor-Black portfolios, which optimize portfolios by considering unsystematic risk, are employed alongside regression analysis to measure how ESG risks influence financial performance.

Berg et al. (2023) demonstrated that aggregated ESG ratings enhance portfolio performance using this framework. However, considering findings from Alves et al. (2023), which showed limited evidence of ESG ratings correlating with global stock returns, subsequent research has substituted ESG ratings with ESG risk factors. This substitution aims to assess the integration effect on financial outcomes in a concentrated portfolio, offering a more nuanced exploration of how ESG considerations influence portfolio dynamics under focused investment strategies. Extensive research suggests that ESG investing did not systematically impact investment performance over the past two decades, highlighting the necessity for a nuanced understanding of integrating ESG factors into effective investment strategies.

2.4 PGGM's 3D Investment Strategy and ESG Integration

PGGM, a not-for-profit cooperative pension fund service provider, has been at the forefront of integrating ESG considerations into its investment processes, driven by its mission to balance financial returns with societal and environmental responsibilities. This strategic orientation reflects the increasing demands from regulators, beneficiaries, and society at large, who expect pension funds to actively contribute to resolving critical global challenges such as climate change while ensuring robust financial performance.

A cornerstone of PGGM's approach is the 3D investment framework, which systematically integrates three critical dimensions—return, risk, and sustainability—into the investment decision-making process. This framework ensures that each investment is assessed not only for its potential to generate financial returns but also for its capacity to manage risks and contribute to sustainable outcomes. PGGM's commitment to ESG integration within this framework makes it a relevant case study for analyzing the impact of ESG risk factors on investment performance. By proactively adapting ESG into its investment process, PGGM aims to enhance the precision and impact of its investment decisions. The analysis of ESG risks within this strategy is not merely theoretical but is applied directly to real-world portfolios, providing a practical evaluation of how these factors influence investment outcomes.

2.5 Assessing the Impact of ESG Risk Ratings

Exploring ESG risk ratings is essential for several reasons. Firstly, risk ratings may provide a clearer indication of how ESG factors could lead to financial loss or create substantial shifts in market perceptions, which are critical for investment decisions. Unlike ESG ratings, which primarily assess compliance and performance against ESG criteria, ESG risk ratings focus on quantifying the potential financial impacts of ESG issues that are not adequately managed. This difference is crucial because it directly ties ESG factors to financial volatility and downside risks, providing a more nuanced understanding of their implications for stock values.

Secondly, risk-oriented metrics could offer investors more precise tools for managing portfolio risk, especially in sectors where ESG issues significantly affect financial performance. For example, industries with high environmental exposure, such as oil and gas, or those under intense regulatory scrutiny, like pharmaceuticals, may benefit from a detailed analysis of ESG risk factors. By incorporating these metrics, investors can identify vulnerabilities and opportunities that traditional ESG ratings might overlook, leading to more informed and strategic investment decisions.

Thirdly, given the limitations found in previous studies regarding the impact of ESG ratings on stock prices, ESG risk ratings might offer a more direct correlation to financial outcomes, thereby enhancing strategic decision-making for investors. Recent studies, such as those by Alves et al. (2023), have shown that while ESG ratings have limited relationships with global stock returns, ESG risk factors have a significant influence on portfolio performance. This indicates that risk ratings could provide a more accurate reflection of the financial implications of ESG factors.

By shifting the focus from broad ESG ratings to specific ESG risk assessments, this research aims to uncover deeper insights into how ESG factors tangibly affect stock prices. This approach provides a more robust framework for investors to evaluate and manage ESG-related risks in their portfolios. The dual approach of evaluating both exposure to ESG risks and the effectiveness of a company's management strategies ensures a comprehensive assessment.

3

Literature Review

The literature on ESG (Environmental, Social, and Governance) investing has expanded significantly in recent years, mirroring the growing interest in sustainable investment practices. This chapter reviews important studies and findings on the growth of ESG investments, the regulatory changes supporting ESG practices, and the effects of ESG factors on financial performance. By exploring current research, this review aims to identify gaps and inconsistencies that underscore the need for further study and standardization in the field.

The existing body of research highlights both the regulatory measures promoting ESG investing and the varied empirical evidence on the financial performance of ESG investments. Despite the increasing adoption of ESG principles, significant questions remain regarding their true financial impact, reflecting a complex and often contradictory landscape of findings.

3.1 ESG Regulatory and Market Dynamics

The regulatory environment has evolved to support and standardize ESG investing practices. In the European Union, regulations such as the Sustainable Finance Disclosure Regulation (SFDR) and the Corporate Sustainability Reporting Directive (CSRD) exemplify this shift. The SFDR mandates that financial market participants disclose how they integrate ESG factors into their investment decisions, promoting greater transparency and accountability. Similarly, the CSRD requires companies to provide detailed sustainability reports, offering investors enhanced access to crucial ESG information. These regulatory measures aim to mitigate risks associated with environmental and social factors, ensuring that financial markets move towards long-term sustainability (Berg et al., 2023; Gantchev et al., 2024; Jacobsen et al., 2019).

Furthermore, international agreements and initiatives, such as the Paris Agreement, have set ambitious targets for reducing carbon emissions, influencing investment strategies worldwide. The emphasis on limiting global warming has catalyzed investments in renewable energy and green technologies, significantly affecting market dynamics and investor behavior. Organizations like the United Nations Principles for Responsible Investment (UN-PRI) have also established benchmarks that promote the integration of ESG factors, further embedding these principles into mainstream investment practices.

3.2 Impact of ESG on Financial Performance

Contradictions exist in research concerning the influence of ESG factors on investment performance, demonstrating the complex relationship between ESG integration and financial outcomes. For example, Khan et al. (2016) a novel dataset was developed by mapping sustainability investments, identified as material for each industry, to firm-specific sustainability ratings using new materiality classifications of sustainability topics. The correlation between these investments and financial performance was examined through calendar-time portfolio stock return regressions and firm-level panel regressions. The findings indicate that firms with high scores on material sustainability issues significantly outperform those with low scores.

Similarly, Henriksson et al. (2019) proposed a method for integrating ESG factors into portfolio construction by focusing on industry-specific material ESG items. They employed a quantitative investment approach, classifying companies into good and bad ESG performers using ESG items deemed material by the Sustainability Accounting Standards Board (SASB). By creating an ESG Good Minus Bad (GMB) factor, they ensured that portfolios were tilted towards good ESG companies while maintaining a large number of positions and small active exposures, thus enhancing the risk-return profile.

Karolyi et al. (2023) further examined the link between ESG practices and financial performance by analyzing the market-based equity greenium across a cross-section of 21,902 firms from 96 countries. They assessed the performance of ”green” stocks versus ”brown” stocks by constructing a green-minus-brown (GMB) portfolio, finding that green stocks generally outperformed brown stocks, particularly in North America before 2016.

Conversely, Liang and Renneboog (2017) and Bolton and Kacperczyk (2022) presented findings that high ESG ratings may have minimal or even negative impacts on stock prices in sectors heavily dependent on carbon emissions. Liang and Renneboog used a multi-factor asset pricing model to evaluate how ESG factors are priced in equity markets, revealing that high ESG ratings are often associated with minimal or negative impacts on stock prices in carbon-intensive sectors. Bolton and Kacperczyk analyzed the global pricing of carbon-transition risk, finding that high carbon emissions are associated with higher expected stock returns, indicating a risk premium for carbon-intensive firms.

The empirical literature on socially responsible investing (SRI) and ESG returns is varied and sometimes inconsistent, raising questions about the true financial impact of these investments. Fama and French (2005) taste model posits that if investors prefer to invest in socially responsible companies, the expected return on such companies will be lower. Similarly, Pastor et al. (2020) developed a model for ESG investing, suggesting that investors' preferences for green assets imply lower returns. Pedersen et al. (2021) introduced the concept of an ESG-efficient frontier, illustrating that ESG factors can either benefit expected returns by conveying information about firm fundamentals or incur costs by affecting investor preferences and constraints.

Additionally, large companies often have a greater capacity to comply with ESG disclosure requirements than smaller firms, due in part to their ability to invest in dedicated sustainable departments focused on ESG reporting. This capacity for enhanced transparency can lead to more favorable ESG ratings and better investor perception and financial performance (Alessandrini & Jondeau, 2019). International enterprises that are cross-listed in various markets may also exhibit resilience to the impacts of country-specific regulations, leveraging their global presence to enhance their reputations by adhering to ESG principles. Cai et al. (2016) indicated that such practices can attract investors who are increasingly attentive to corporate governance and sustainability issues.

3.3 Methodological Review

Research methods for investigating the impact of ESG factors on stock prices include both qualitative and quantitative approaches. Qualitative methods, such as interviews, case studies, and modeling, play a crucial role in helping stakeholders comprehend the significance of ESG issues and develop effective implementation strategies within companies. These methods provide in-depth insights into the qualitative aspects of ESG impacts, facilitating a richer understanding of corporate sustainability practices and their integration into business strategies.

For example, qualitative research can reveal how cultural backgrounds influence the interpretation of ESG news. As seen in the findings of Vincentiis (2022), bad news impacts stock prices more in Europe, while good news has a greater effect in the USA, illustrating the varying cultural and economic interpretations of ESG factors. This highlights the importance of contextualizing ESG impacts within regional and cultural frameworks.

On the quantitative side, investors, particularly those in the financial sector, seek to establish a numerical relationship between ESG scores and stock prices. Historically, a straightforward method for addressing ethical investment concerns involved excluding ”sin” stocks, such as those in the tobacco and alcohol industries. This approach was one of the earliest forms of ESG-conscious investing, reflecting an initial, direct method to align investment portfolios with certain ethical standards (Alessandrini & Jondeau, 2019).

Subsequent advancements in ESG evaluation introduced several quantitative frameworks. Khan et al. (2016) established an initial ESG dataset and utilized panel analysis to demonstrate a positive relationship between ESG ratings and stock prices. Berg et al. (2021) proposed two-staged least square regression to measure the correlationship between different rating agencies. Building on this, Lo and Zhang (2023) incorporated impact factors into a Fama-French based model and proposed a Treynor-Black based portfolio construction method, while Berg et al. (2023) adopted this framework to examine model performance using aggregated ESG ratings from six leading rating agencies. However, the most recent comprehensive analysis by Alves et al. (2023), which covered over 16,000 stocks and spanned 20 years of data from seven rating providers, indicated that ESG ratings have a limited relationship with stock prices. This study employed Fama-MacBeth regressions and included an extensive set of control variables to rigorously analyze the data, yet found very little evidence that ESG ratings are related to future stock returns globally.

To further enhance these methodologies, this study proposes the integration of ESG risk factors into asset pricing models. This shift aims to capture the dynamic nature of ESG-related risks and their direct impact on financial performance. The Lo and Zhang (2023) framework will be adapted to incorporate these risk factors, providing a more comprehensive approach to evaluating a company’s long-term sustainability and financial performance. Moreover, this study will test the robustness of the model by including external economic factors such as oil prices, to ensure that the investment strategy is resilient to broader market fluctuations.

3.4 Quantifying ESG Impact

The approach proposed by Lo and Zhang (2023) extends traditional asset pricing models by incorporating ESG risk factors as external variables. This innovative methodology is designed to adjust expected returns based on the potential impact of environmental, social, and governance issues on a company’s financial performance. The primary objective is to provide a more accurate and robust forecast of asset returns, thereby enabling more informed and strategic investment decisions.

The methodology begins with the quantification of excess returns, also known as alphas, for individual stocks ranked by their ESG scores. This ranking is crucial as it directly influences the optimization process for constructing ESG portfolios. By ranking stocks according to their

ESG scores, the model can effectively adjust portfolio weights to maximize returns while considering ESG factors.

Lo and Zhang (2023) framework utilizes a multi-factor model, such as the Fama-French factor model, to describe the relationship between stock returns and various risk factors. The model accounts for the risk-free rate, factor returns, and the stock's sensitivity to these factors. This allows for a comprehensive analysis of how ESG factors influence stock performance beyond traditional financial metrics.

A key aspect of the methodology is the use of Treynor-Black portfolios. These portfolios are designed to optimize risk-adjusted returns by focusing on unsystematic risk, which is specific to individual stocks and can be mitigated through diversification. The expected excess returns are derived from the ranked alphas, and the portfolio weights are optimized to maximize the Sharpe ratio. This approach ensures that the portfolios are not only aligned with ESG principles but also optimized for financial performance.

To implement this, the model performs a series of time series regressions using daily returns to estimate the alpha for each stock. This involves evaluating the expected values, variances, and covariances of the ranked alphas, which are influenced by their ESG scores. The model then estimates parameters such as the cross-sectional correlation between alphas and ESG scores, and the standard deviation of alphas. These parameters are critical for constructing the optimal Treynor-Black portfolios.

The advantage of the Lo and Zhang (2023) approach lies in its robustness and simplicity. Unlike traditional Markowitz portfolios, which often produce unstable weights due to the need for estimating a large number of parameters, the Treynor-Black approach requires only a few key parameters. This makes the model more practical and reliable for real-world applications.

Finally, the model provides a forward-looking estimate of portfolio alpha, referred to as the model-implied alpha. This is validated empirically against realized alpha, computed using a multi-factor model like the Capital Asset Pricing Model (CAPM), the Fama-French three-factor model (FF3), or the Fama-French five-factor model (FF5). By comparing the model-implied alpha with realized alpha, the approach ensures that the predictions are grounded in actual financial performance.

3.5 Identification of Research Gap

The literature on ESG investment reveals several gaps that require further investigation(Alessandrini & Jondeau, 2019; Alves et al., 2023; Berg et al., 2023; Gantchev et al., 2024; Lo & Zhang, 2023). Despite the significant growth and integration of ESG factors into investment strategies, discrepancies remain concerning the financial performance and impact of ESG investments across various sectors and regions.

Firstly, while some studies indicate that ESG integration enhances risk-return profiles and can lead to superior financial returns, others suggest minimal or negative impacts, particularly in sectors heavily reliant on carbon emissions. This inconsistency highlights the need for more detailed research that takes into account the differences in ESG impacts across various industries and regions.

Secondly, the empirical evidence on the financial returns of socially responsible investing (SRI) and ESG investments is varied and sometimes contradictory. This variability arises from different definitions of impact, time periods, asset classes, and asset-pricing models used in the analyses. The wide range of empirical estimates for ESG returns highlights the necessity for a standardized framework to better measure and compare the financial impacts of ESG investments.

Additionally, the capacity for ESG compliance and disclosure varies significantly between large and small companies. Larger firms, with more resources, are often better positioned to meet ESG requirements and thus receive higher ESG ratings, potentially skewing performance evaluations. This discrepancy suggests a need for research that accounts for company size and the differing capabilities in meeting ESG standards.

Moreover, existing methodologies for assessing the impact of ESG on stock prices, while comprehensive, still leave room for improvement. The use of multi-factor models and sophisticated portfolio construction methods like those proposed by Lo and Zhang (2023), although advanced, require further empirical validation across different market conditions and economic environments to confirm their robustness and reliability.

3.6 Conceptualization

The methodology for assessing the impact of ESG (Environmental, Social, and Governance) risk factors on investment portfolios is a comprehensive, iterative process. This process integrates ESG factors into financial analysis and investment strategy, providing insights into their impact on financial performance and allowing for continuous improvement.

Data Collection and Preprocessing

The initial phase involves rigorous data collection and preprocessing, focusing on identifying and evaluating important ESG risk factors from the Aladdin database. Historical data will be analyzed using correlation analysis and feature ranking models to identify the most relevant

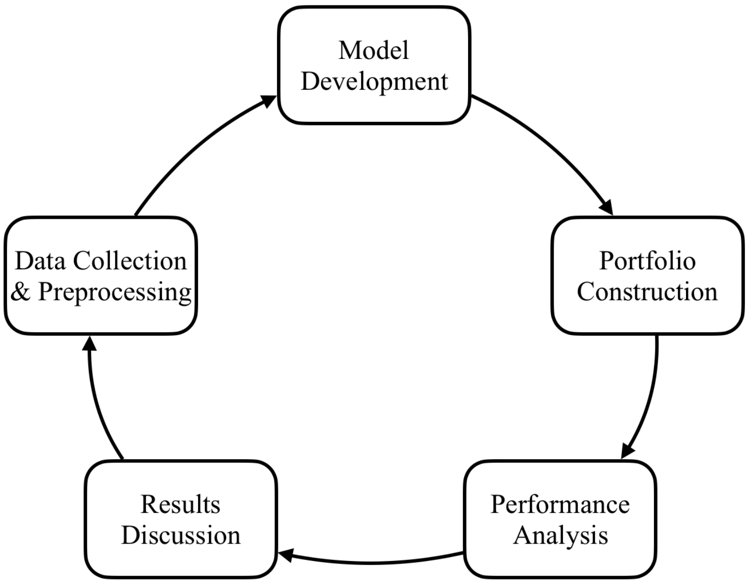


Figure 3.1: Conceptualisation Graph

ESG factors. These factors include environmental issues like climate change and pollution, social aspects such as working conditions and community engagement, and governance issues, including board composition and shareholder rights. The potential financial impact of ESG issues on a company's economic value will be assessed using metrics provided by Sustainalytics, which evaluates a company's exposure to and management of ESG issues.

Model Frameworks

Following data collection, the study will employ several model frameworks to analyze the data. The Capital Asset Pricing Model (CAPM) will be used to determine the expected return of an asset based on its market risk. The Fama-French Three-Factor Model (FF3) will extend this analysis by incorporating size and value factors to better explain variations in stock returns. An extended model will integrate ESG factors into the Fama-French framework, providing a more detailed understanding of how ESG considerations affect financial metrics and portfolio performance.

Portfolio Construction

In the portfolio construction phase, the analyzed data will be used to create and optimize portfolios that incorporate ESG considerations. This involves using regression analysis to explore the relationship between ESG risk metrics and investment performance. Portfolios will be constructed using strategies such as quintile-based sub-portfolios and optimized Treynor-Black models to effectively integrate ESG factors, aiming to enhance both financial and ESG performance.

Performance Analysis

The final phase involves the performance analysis of the constructed portfolios using various metrics, such as the Sharpe ratio and Sortino ratio. This analysis will provide insights into the impact of ESG factors on risk-adjusted returns, evaluating the effectiveness of integrating ESG considerations into investment strategies. The performance analysis will help determine whether ESG integration can lead to superior financial performance and more sustainable investment outcomes.

Results Discussion

The results discussion will interpret the findings from the performance analysis, linking them back to the research questions and theoretical framework. It will explore how well the integration of ESG factors into investment strategies aligns with the expected financial performance and societal benefits. Additionally, the discussion will address any discrepancies or unexpected outcomes, providing possible explanations and implications for future research and practical applications in ESG investing. This section will highlight the study's contributions to the literature and suggest areas for further investigation.

After the results discussion, the insights gained will feed back into the data collection and preprocessing phase. This iterative loop allows for the continuous refinement of models and investment strategies based on new data, evolving ESG criteria, and changes in market dynamics. By continuously updating and improving the methodology, the investment strategy remains adaptive and responsive to emerging trends and developments in ESG factors.

4

Data Description

This chapter provides a detailed description of the data used to assess the impact of Environmental, Social, and Governance (ESG) risk factors on investment portfolios. It outlines the ESG ratings sourced from Sustainalytics, climate risk evaluations from BlackRock's Aladdin platform, and financial performance metrics from PGGM's internal database. The dataset spans a four-month period from January 2024 to April 2024, covering equities' daily returns and benchmark data from the FTSE World Index and its sub-indices.

4.1 ESG Ratings

ESG factors refer to elements that impact a company's operations and its ability to create long-term value. These factors cover a wide range of issues, such as climate change policies, labor practices, corporate governance structures, and community engagement. They are used to evaluate a company's sustainability and ethical impact.

ESG factors are criteria used to assess a company's operations and policies in three critical areas:

Factor	Description
Environmental	This includes how a company interacts with the environment. Key issues involve climate change, resource depletion, waste, pollution, and deforestation. Companies with strong environmental practices aim to minimize their negative impact on the planet.
Social	This concerns the company's relationships with employees, suppliers, customers, and communities. Key issues include working conditions, health and safety, employee relations, diversity, and community engagement. Companies scoring well on social factors tend to foster positive relationships and support their stakeholders.
Governance	This refers to how a company is governed. Key issues include board composition, executive pay, audits, internal controls, and shareholder rights. Good governance ensures a company operates with integrity and transparency.

Table 4.1: ESG Factors and their Descriptions

ESG factors are important in investment decisions because they provide a comprehensive view of a company's long-term sustainability and ethical impact. They can affect investment portfolio performance in several ways:

Impact	Description
Risk Management	Companies with poor ESG practices may face regulatory fines, legal issues, and reputational damage, negatively impacting their financial performance.
Operational Efficiency	Companies that manage their ESG risks well often operate more efficiently, reducing operational costs and improving employee satisfaction and productivity.
Investment Returns	Integrating ESG factors into investment analysis can help identify companies likely to perform well over the long term, leading to higher investment returns.

Table 4.2: Impact of ESG Factors on Investment Decisions

4.2 ESG Risk Factors

To clarify the relationship between ESG factors and ESG risk factors: ESG factors refer to a broad set of criteria used to evaluate a company's overall sustainability and ethical impact.

These include environmental practices, social responsibilities, and governance structures. Investors use ESG factors to identify companies with strong sustainability practices that are likely to offer long-term value and stability.

In contrast, ESG risk factors specifically assess the potential financial risks related to ESG issues that could negatively impact a company's economic value. This involves evaluating a company's exposure to ESG risks and its effectiveness in managing these risks. Investors use ESG risk factors to quantify the degree of financial risk posed by ESG issues, helping them avoid or mitigate investments in companies with poor ESG risk management.

Thus, while ESG factors provide a holistic view of a company's sustainability practices, ESG risk factors focus on the financial implications of ESG-related risks, guiding investors in managing potential downsides in their portfolios.

The ESG Risk Ratings by Sustainalytics integrate two critical dimensions: exposure to ESG factors and the effectiveness of a company's management strategies in handling these risks. This dual approach ensures a comprehensive evaluation of how environmental, social, and governance issues impact a company's economic value and sustainability performance.

Dimension	**Description**
Exposure Dimension	This evaluates a company's sensitivity or vulnerability to various ESG risks, assessing the significance of each ESG factor to the company's overall risk profile and determining their potential impact on financial performance.
Management Dimension	This assesses how well a company manages its exposure to ESG risks, examining the company's policies, programs, and performance metrics related to ESG issues. It includes a detailed analysis of the company's management systems and responses to past incidents or controversies.

Table 4.3: Dimensions of ESG Risk Ratings by Sustainalytics

By focusing on ESG risk ratings, this research provides a more precise and actionable framework for investors, helping them better understand and mitigate the potential financial impacts of ESG factors.

4.3 Data Selection

The process of selecting data for the model involved a detailed examination of correlation patterns, visualized through a heatmap 4.1, followed by a multicollinearity check using Variance

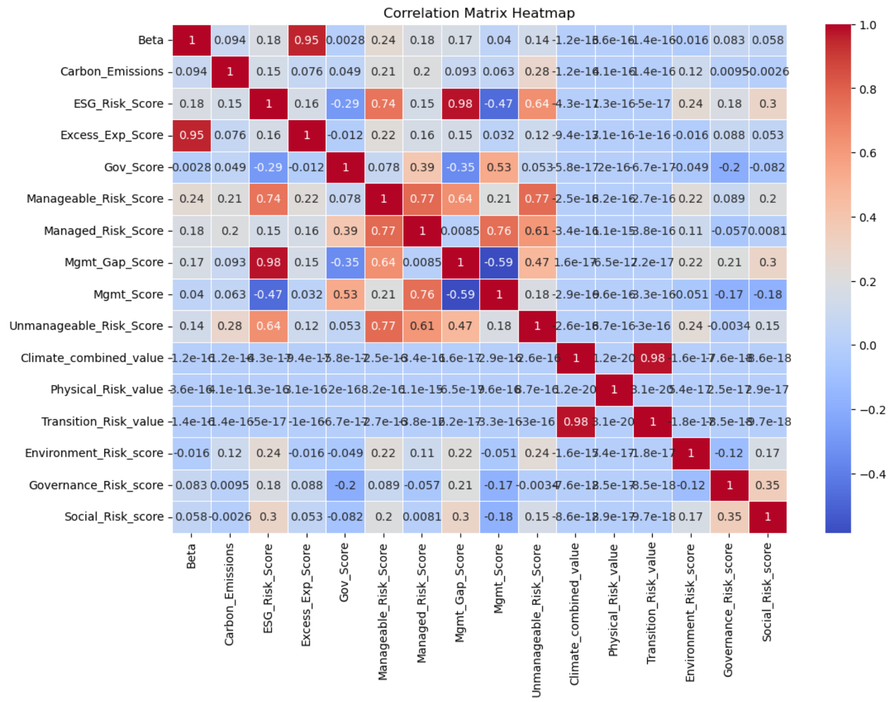


Figure 4.1: Correlation Analysis Results

Feature	VIF
Constant	8768.369
Beta	11.365
Carbon Emissions	1.123
ESG Risk Score	∞
Excess Exp Score	11.240
Gov Score	1.445
Manageable Risk Score	∞
Managed Risk Score	∞
Mgmt Gap Score	∞
Mgmt Score	13.544
Unmanageable Risk Score	∞
Climate Combined Value	24.730
Physical Risk Value	1.000
Transition Risk Value	24.730
Environment Risk Score	1.150
Governance Risk Score	1.257
Social Risk Score	1.265

Table 4.4: Variance Inflation Factor (VIF) for Different Features (Before Removal)

Inflation Factor (VIF) values. The initial step was to conduct a correlation analysis, which helped in identifying variables that were highly correlated with one another. These correlations were visually represented in a heatmap, where variables exhibiting strong interrelationships were highlighted. Such high correlations often suggest that certain variables may not provide unique information to the model, thereby increasing the risk of redundancy.

Feature	VIF
Constant	6286.004
Beta	11.247
Carbon Emissions	1.034
Excess Exp Score	11.210
Gov Score	1.434
Mgmt Score	1.442
Environment Risk Score	1.093
Governance Risk Score	1.237
Social Risk Score	1.225

Table 4.5: Variance Inflation Factor (VIF) for Different Features (After Removal)

To further investigate these relationships, VIF values were calculated for each variable. The VIF is a diagnostic measure that quantifies how much a variable's variance is influenced by its correlation with other variables. In this case, several variables, including 'ESG Risk Score,' 'Manageable Risk Score,' 'Managed Risk Score,' 'Mgmt Gap Score,' 'Unmanageable Risk Score,' 'Climate Combined Value,' 'Transition Risk Value,' and 'Physical Risk Value,' were found to have excessively high VIF values. This indicated a high degree of multicollinearity, where these variables are essentially overlapping in the information they provide.

Given these findings, it was necessary to exclude these variables from the model. Removing them not only reduces redundancy but also enhances the model's stability and interpretability. By eliminating these collinear variables, the model is less prone to overfitting, making it more reliable when applied to new data.

4.4 Data Description

ESG risk data are sourced from BlackRock's portfolio management platform, Aladdin. This dataset includes ESG risk metrics provided by Sustainalytics and incorporates climate risk evaluations from the Aladdin Climate Risk model. The data is detailed at a daily level, spanning a four-month interval from January 2024 to April 2024, for each equity under consideration. This period was chosen due to the availability of ESG risk data.

Daily return data for equities predominantly from developed markets are obtained from PGGM's internal database. The FTSE World Index serves as the benchmark for overall equity performance. Sub-portfolios focusing on developed and emerging markets are benchmarked against the respective FTSE Developed Market Index and FTSE Emerging Market Index. The 3-month U.S. Treasury rate is employed as the risk-free rate in calculations. For the analysis of excess returns, factors are utilized from the Fama-French data library, ensuring a robust and academically recognized framework for financial modeling.

The dataset employed in this analysis comprises various financial and ESG metrics for a selection of securities. Key variables, as outlined in Table 4.7 , include the Beta, Carbon Emissions, Excess Exposure Score, Governance Score, Management Score, Environment Risk Score, Governance Risk Score, and Social Risk Score. Additionally, the dataset includes daily stock returns, portfolio weight, daily FTSE returns, and Fama-French factors such as Mkt-RF, SMB, and HML. Table 4.6 provides an example of this dataset.

Metric	**2023-12-29**	**2023-12-28**	**2023-12-27**
CUSIP	SB1YW4404	SB1YW4404	SB1YW4404
Security	3I GROUP PLC	3I GROUP PLC	3I GROUP PLC
Beta	0.957353	0.957353	0.957353
Carbon Emissions	377.000	377.000	377.000
Excess Exp	-1.450	-1.450	-1.450
Gov Score	62.87	62.87	62.87
Mgmt Score	71.77	71.77	71.77
Env Risk	4.67	4.67	4.67
Gov Risk	7.19	7.19	7.19
Soc Risk	8.53	8.53	8.53
Return	-0.006565	-0.002047	0.008674
Weight	0.000433	0.000436	0.000438
Daily Return	0.320690	0.225736	-0.015433
FTSE Return	0.313835	0.240446	-0.188501
Mkt-RF	0.292835	0.219446	-0.209501
SMB	-1.13	-0.36	0.14
HML	-0.37	0.02	0.12

Table 4.6: Example Data Structure

Feature	Description
Beta	This factor quantifies the extent to which a company's overall exposure diverges from that of its subindustry. It is calculated by dividing the company's overall exposure by the average exposure within the subindustry, which can be weighted by market capitalization or calculated equally across all companies in the subindustry.
Carbon Emissions	This metric assesses the firm's emissions profile, specifically focusing on greenhouse gases, such as CO2 equivalents. It measures the emissions produced per million dollars of sales, encompassing Scope 1 (direct emissions) and Scope 2 (indirect emissions from purchased energy) greenhouse gas emissions.
Excess Exposure Score	This score measures the deviation of a company's exposure from the subindustry average. It is calculated by subtracting the subindustry exposure score from the company's exposure score. A positive score indicates that the company's exposure exceeds the subindustry average, whereas a negative score suggests it is lower.
Gov Score	The governance score evaluates the risks and opportunities associated with a company's governance practices, which may impact its ability to successfully implement its business strategy. The overall governance score is computed as a weighted average of key governance-related issues.
Mgmt Score	The management score reflects the effectiveness of a company's management of ESG risks across various issues. The score ranges from 0 to 100, with higher scores denoting stronger management practices. It is calculated by combining the weighted corporate governance score with the weighted scores of other management issues.
Environment Risk Score	This score evaluates the degree of risk posed to a company's economic value by environmental factors. It forms part of the broader ESG risk assessment, specifically focusing on environmental risks.
Governance Risk Score	The governance risk score assesses the potential risk to a company's economic value from governance-related factors. It is derived from a combination of corporate governance metrics and governance-related material ESG issues.
Social Risk Score	This score measures the risk to a company's economic value arising from social factors. It is a component of the overall ESG risk rating, emphasizing social aspects that may influence the company's operations and value.

Table 4.7: Descriptions of Key Features Used in the Analysis

5

Methodology

This chapter outlines the comprehensive approach employed to assess the impact of ESG (Environmental, Social, Governance) risk factors on investment portfolios. The methodology begins with data collection and preprocessing, which includes normalization, multiple imputation for missing values, and outlier mitigation to ensure reliability. Principal Component Analysis (PCA) is then applied to reduce the dimensionality of the ESG data, followed by the Fama-MacBeth regression to estimate risk premia. Subsequently, the impact of ESG risk factors on excess returns is quantified using an extended Fama-French model and Lo and Zhang (2023) computational framework. Finally, top-down and Treynor-Black weighted portfolios are created to compare the performance of different financial models in incorporating ESG factors. This methodical evaluation aims to assess the effectiveness of the models and strategies for integrating ESG considerations into investment decision-making.

5.1 Data Collection and Preprocessing

The primary data sources for this study include ESG ratings from the Sustainalytics and Aladdin Climate Risk databases, financial performance metrics from PGGM's internal database, oil price indicators from Bloomberg, and daily exchange rates. The dataset spans a four-month period from January 2024 to April 2024, covering key variables such as ESG scores, local returns, and market benchmarks. These data sources are chosen for their comprehensive coverage of ESG factors across various industries and geographies and their credibility.

To prepare the data for analysis, several preprocessing steps were undertaken. First, all data analysis was conducted using Python. The data was categorized and extracted to facilitate analysis, involving the structuring of data into a time series format suitable for statistical analysis, ensuring all variables were correctly aligned and consistently recorded.

Next, Z-score normalization was applied to each variable. This process adjusts the data to have a mean of zero and a standard deviation of one, preventing variables with larger ranges from unduly influencing the results. Normalization ensures that all variables are on a comparable scale, which is essential for accurate correlation and regression analyses.

Handling missing values is a critical step in the preprocessing stage. Multiple imputation methods were used to address missing data points in the ESG risk metrics. These methods estimate missing values based on available data, specifically calculating imputed values based on the historical data of the respective stocks, ensuring the completeness of the dataset without introducing significant biases. This approach enhances the reliability of the analysis by maintaining data integrity.

Outlier mitigation is also an essential part of the preprocessing process. Outliers were identified and addressed to minimize their impact on the analysis. Extreme values that could skew the results were excluded from the dataset, maintaining data robustness. This step is crucial in ensuring that the analysis reflects true underlying patterns rather than being distorted by anomalous data points.

5.2 Evaluation of Materiality

Principal Component Analysis (PCA):

The materiality and quality of the risk data are evaluated, with materiality defined as the ability of data to alter the decision of a reasonable investor. The dataset includes various ESG risk factors, such as individual E, S, and G scores, and the transition and physical risks associated with each stock.

In this study, PCA will be employed to streamline the ESG dataset by reducing its dimensionality while preserving the most critical information. This method will transform various ESG measures, such as exposure, emissions, and industry rankings, into a single composite score for each stock. This aggregated score will simplify the analysis and maintain the integrity of the original data, ensuring that the primary variance is captured effectively.

$$\text{ESG}_{i,\text{PCA}} = \text{PCA}(\text{ESG}_{i,\text{exposure}}, \text{ESG}_{i,\text{emission}}, \ldots, \text{ESG}_{i,\text{rank}})$$

The use of PCA is favored over other methods such as factor analysis due to its robustness in handling multicollinearity among variables and its efficiency in reducing data without significant information loss. PCA helps in aggregating data effectively and reducing noise, making the analysis more reliable. This method ensures that the most crucial components are retained based on their variance contribution, providing a more objective and straightforward method for data reduction. Consequently, PCA will enhance the effectiveness of the ESG risk integration into the quantitative models, ultimately leading to more informed and strategic investment decisions.

Fama-MacBeth Regression:

The Fama-MacBeth regression is a two-step procedure used to estimate the risk premia associated with different factors. In the first step, cross-sectional regressions are conducted each period to estimate factor loadings. The cross-sectional regression for a given period t is:

$$R_{i,t} = \alpha_t + \beta_{1,t} \cdot X_{1,i} + \beta_{2,t} \cdot X_{2,i} + \ldots + \beta_{k,t} \cdot X_{k,i} + \epsilon_{i,t}$$

where $R_{i,t}$ is the return of asset i at time t, $X_{k,i}$ represents the k-th factor for asset i, $\beta_{k,t}$ is the factor loading for the k-th factor at time t, and $\epsilon_{i,t}$ is the error term.

In the second step, time-series regressions of these factor loadings on returns are performed to estimate the average risk premia. The time-series regression for the factor loadings is:

$$\hat{\beta}_{k,t} = \gamma_k + \epsilon_t$$

This method provides robust estimates of the risk premiums by accounting for time-series variation in the cross-section of stock returns, making it a valuable tool for assessing the impact of ESG factors on expected returns.

5.3 Quantify the Excess Return with Material Risks

A computational framework advanced by Lo and Zhang (2023) is utilized, which builds on the foundational principles of the Fama-French multi-factor model to quantify the financial impact of impact investing. The Fama-French model introduced by Eugene Fama and Kenneth French, is a cornerstone in financial economics which enhances the Capital Asset Pricing Model by incorporating additional factors.

Asset Pricing Model:

The Capital Asset Pricing Model (CAPM) is a foundational financial model used to determine the expected return of an asset based on its risk relative to the market. However, critiques by Fama and French highlight its limitations, such as reliance on a single factor (market risk) and the instability of beta over time (Fama & French, 1992, 1993, 1995, 1996, 1998).

To address these limitations, the Fama-French Three-Factor Model (FF3) incorporates additional factors like size and value premiums, thus providing a more comprehensive explanation of stock returns. The FF3 model is defined by the following equation:

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_i \cdot SMB_t + h_i \cdot HML_t + \epsilon_{it}$$

where R_{it} represents the return of stock i at time t, R_{ft} is the risk-free rate, and R_{mt} is the overall market return. The coefficients β_i, s_i, and h_i measure the sensitivity of stock i's returns to the market excess return, the size factor (SMB), and the value factor (HML), respectively. The term α_i captures the stock's excess return relative to what the three-factor model predicts, and ϵ_{it} represents the residual error.

Furthermore, recent research by Lo and Zhang (2023) extends the FF3 model by incorporating ESG factors, and Berg and Lo demonstrate that portfolios with higher ESG ratings can yield superior returns, highlighting the relevance of ESG considerations in modern investment strategies (Berg et al., 2021).

Lo and Zhang quantitative method:

The methodology proposed by Lo and Zhang (2023) for quantifying excess returns in ESG portfolios involves several steps. First, a multi-factor model, such as the Fama-French model, is used to describe the returns of N stocks, denoted by R_{it}, where

$$R_{it} - R_{ft} = \alpha_i + \sum_{k=1}^{K} \beta_{ik}(\Lambda_{kt} - R_{ft}) + \epsilon_{it}$$

with $E[\epsilon_{it}|\Lambda_{kt}] = 0$ for all k.

Here, R_{ft} is the risk-free rate, α_i and β_{ik} are the excess return and factor betas respectively, Λ_{kt} is the k-th factor return, and ϵ_{it} is the idiosyncratic return component.

To incorporate ESG factors, ESG investors rank stocks by their ESG scores, ESG_i, and the alpha of the i-th ranked stock is denoted by $\alpha_{[i:N]}$. Lo and Zhang (2023) derive formulas for the expected values, variances, and covariances of these ranked alphas:

$$E(\alpha_{[i:N]}) = \sigma_\alpha \cdot \rho \cdot E(Y_{i:N})$$

$$Var(\alpha_{[i:N]}) = \sigma_\alpha^2 \cdot (1 - \rho^2 + \rho^2 \cdot Var(Y_{i:N}))$$

$$Cov(\alpha_{[i:N]}, \alpha_{[j:N]}) = \sigma_\alpha^2 \cdot \rho^2 \cdot Cov(Y_{i:N}, Y_{j:N})$$

where ρ is the cross-sectional correlation between α_i and ESG_i, σ_α is the standard deviation of α_i, and $Y_{1:N} < Y_{2:N} < \cdots < Y_{N:N}$ are the order statistics of N independent and identically distributed standard Gaussian random variables.

To estimate these formulas, a time series regression is performed annually to estimate α_i for each stock. Parameters ρ and σ_α are then estimated based on ESG_i and the estimated α_i. Moments related to $Y_{i:N}$ are calculated through simulations of N standard normal random variables.

These results are instrumental in constructing optimal Treynor-Black portfolios that maximize the Sharpe ratio of ESG portfolios. The expected excess returns, $E(\alpha_{[i:N]})$, are crucial for determining portfolio weights. This framework is robust as it requires estimating only two parameters, ρ and σ_α, compared to traditional Markowitz portfolios.

Additionally, the model allows for quantifying the excess return of any ESG portfolio, α_p, with weights ω_i:

$$E(\alpha_p) = \sum_{i=1}^{N} \omega_i E(\alpha_{[i:N]}) = \rho\sigma_\alpha \sum_{i=1}^{N} \omega_i E[Y_{i:N}]$$

This provides an estimate of the alpha for ESG portfolios, referred to as the model-implied alpha. This alpha is validated empirically against a forward-looking estimate of alpha, which is computed using a multi-factor model and future returns.

ESG integrated FF3 model:

To further enhance the analysis, the extended Fama-French model incorporating an ESG factor is considered. The formula for this model is:

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_i \cdot SMB_t + h_i \cdot HML_t + e_i \cdot ESG_i + \epsilon_{it}$$

This equation integrates a specific ESG factor (ESG_i), where e_i measures the sensitivity of the stock returns to ESG influences, suggesting that ESG integration can significantly affect the risk-return profile of a portfolio.

However, recent research challenges the direct relevance of ESG ratings to stock prices, suggesting that the impact might be overstated or inconsistent. This critique prompts a reevaluation of how ESG factors are incorporated into asset pricing models. Instead of generic ESG ratings, the focus is shifting towards *material ESG risks*, which are likely more indicative of potential financial impacts specific to each industry or company (Khan et al., 2016). By replacing a generic ESG target with a more detailed approach that considers material ESG risks, the model aims to more accurately depict how ESG factors influence excess returns and contribute to the overall risk and return dynamics of portfolios.

Such an approach not only refines the model's predictive accuracy but also aligns better with the principles of materiality in financial analysis, suggesting that not all ESG factors are uniformly impactful across different sectors. This detailed incorporation can reveal more about the complex ways sustainability-related factors interact with financial performance, providing deeper insights for investors dedicated to including ESG considerations in their investment decisions.

5.4 Portfolio Creation

The portfolios are split based on the stocks' ESG risk performance into three top-bottom portfolios covering 10%, 25%, and 40% of the portfolio. Each portfolio's alpha is aggregated by the weighted average value of the stocks' alpha.

The advantages of top-bottom portfolio analysis are significant: investors can spread ESG risks at different levels. For instance, portfolios covering the top 10% focus on stocks with extreme ESG risks, while those covering 40% are generally more diversified. By comparing the performance of these portfolios, investors can adjust their strategies flexibly. When creating the top-bottom portfolios, the weight of each stock is crucial based on the research's aim. Retaining the original stock weights ensures that the top-bottom portfolios do not alter the original portfolio's exposure and risks. Equal-weight portfolios, on the other hand, focus more on the influence of ESG risk factors, directly revealing the ESG-integrated effect. In this analysis, the top-bottom portfolios are created by retaining the original weights from the company portfolio to evaluate the real impact of ESG risk factors.

Treynor Black weighted Porfolios:

The Treynor-Black model is an optimization approach that adjusts portfolio weights based on the expected excess returns (implied alpha) of individual stocks. This model ranks stocks according to their implied alpha, with higher-ranked stocks expected to have better risk-adjusted returns and thus given greater weights. Specifically, Lo and Zhang (2021) show that the weight of the i-th ranked stock in a universe of N stocks can be approximated by the following equation:

$$\omega_i \propto \Phi^{-1}(\zeta_i)$$

where $\zeta_i = \frac{i}{N}$ and Φ^{-1} is the inverse of the cumulative standard normal distribution. This approximation holds when the number of stocks is large and stocks have identical idiosyncratic volatilities. For example, in the top 10% (percentiles 90 to 100) of an equal-weighted portfolio, all stocks are given equal weights. However, in Treynor-Black weighting, higher-ranked stocks are given larger weights than lower-ranked stocks if the correlation ρ between the ESG score and stock alpha is positive.

Once these ESG portfolios are constructed, they can be combined further with any other portfolio. A common application is to combine the active (ESG) portfolio with a passive index, such as the market portfolio. The returns of the combined portfolio are given by:

$$r_{active+passive} = \omega_A \cdot r_{active} + (1 - \omega_A) \cdot r_{passive}$$

where r_{active} can be any return of a top-bottom equal-weighted or Treynor-Black weighted portfolio, $r_{passive}$ is the return of the passive portfolio (e.g., the market index), and ω_A is the weight of the active portfolio. In this analysis, ω_A is fixed at 0.5 as an illustrative example.

Portfolio Type	**Description**
Company Portfolios	Portfolios that follow PGGM's original stock weights.
Top-Bottom Portfolios	Portfolios divided into different quintiles to examine performance across varying levels of ESG risk exposure.
Treynor-Black Portfolios	Both equal-weighted and optimized Treynor-Black portfolios are used to investigate the impact of ESG factors on risk-adjusted returns.

Table 5.1: Final Set of Portfolios

Each portfolio construction method has a distinct focus. Using the company's original weights ensures that the portfolio's exposure and risk characteristics remain consistent with the original investment strategy. This method focuses on evaluating the real impact of ESG risk factors without altering the inherent risk structure of the portfolio.

On the other hand, the Treynor-Black weighted portfolios emphasize optimizing the portfolio based on expected excess returns, integrating ESG factors to maximize the Sharpe ratio and improve risk-adjusted returns. This approach allows for a more dynamic adjustment of portfolio weights, reflecting the performance potential of stocks as indicated by their implied alphas.

By comparing these approaches, investors can gain a comprehensive understanding of the impact of ESG factors. The company's original weights method offers insights into maintaining existing risk exposures while integrating ESG considerations. The Treynor-Black method provides a way to enhance returns through optimization, and the top-bottom portfolio analysis highlights the performance of different ESG risk segments, facilitating strategic adjustments.

5.5 Model Evaluation

To conduct a comprehensive assessment of the performance of investment portfolios that incorporate ESG risk factors, this analysis compares the efficacy of several financial models: the CAPM, the Fama-French Three-Factor Model (FF3), the Fama-French model augmented with ESG factors (FF+ESG), and the Lo and Zhang (2023) model. This comparative approach aims to identify which models most effectively capture the impact of ESG integration on portfolio returns and risk.

Alpha Distribution Analysis

The distribution of alpha values is analyzed using histograms and frequency distributions to evaluate the consistency and variability of each model's performance. By examining the spread and concentration of these alpha values, we can determine whether the models produce stable and reliable alpha predictions or if they are susceptible to significant fluctuations.

Alpha Analysis for Top-Bottom Portfolios

To analyze the impact of ESG scores, top-bottom portfolios are created, representing 10%, 25%, and 40% of the portfolio. Stocks are ranked based on their ESG scores, and the top and bottom performers are selected within each category. The performance of these portfolios is measured and compared by normalizing the alpha values, ensuring comparability across different portfolio sizes. This methodology helps elucidate how varying concentrations of ESG characteristics influence portfolio performance.

Normalized Total Alpha and Model Performance

Normalized total alpha values are calculated for different portfolio sizes to ensure comparability across the models. Normalization adjusts the alpha values relative to the scale and composition of the portfolios, allowing for a fair evaluation of the CAPM, FF3, FF+ESG, and Lo and Zhang (2023) models in capturing risk-adjusted excess returns.

Beta and R-Squared Analysis

The sensitivity of portfolio returns to various risk factors is evaluated by analyzing the beta coefficients and R-squared values of the linear models. Beta coefficients indicate the sensitivity of portfolio returns to market, size, and value factors, while R-squared values measure the proportion of variance in returns explained by the models. This analysis provides insights into the explanatory power of each model and identifies which models are more effective in capturing the complexities of ESG-integrated portfolios.

Random Forest Model Implementation

The Random Forest (RF) model is implemented to capture complex interactions between variables. This non-linear model is compared with linear models to evaluate its performance. Importance scores are calculated to understand the significance of different factors, providing a detailed assessment of the variables influencing portfolio returns.

Weighted Treynor-Black Portfolio Analysis

The analysis includes the evaluation of the Weighted Treynor-Black Portfolio, which differs from typical company portfolios in its construction. This portfolio assigns weights based on the inverse cumulative distribution function of ESG score rankings, favoring stocks with higher ESG scores. By optimizing alpha and managing beta, this approach aims to create a portfolio that closely aligns with expected market returns, similar to the Lo and Zhang (2023) model. The performance similarity between the Treynor-Black and Lo and Zhang (2023) models is examined to understand their optimization strategies, which aim to minimize idiosyncratic risk and enhance the Sharpe ratio by combining an active portfolio with a market portfolio.

Through this detailed and methodical evaluation, the study seeks to identify the models and strategies that most effectively integrate ESG factors, providing valuable insights for investors aiming to enhance their risk-adjusted returns through sustainable investment practices.

6

Result and Discussion

This chapter aims to compare the alpha predictions of four financial models: the Capital Asset Pricing Model (CAPM), the traditional Fama-French 3-Factor model (FF3), a Fama-French model integrated with Environmental, Social, and Governance (ESG) factors through Principal Component Analysis (PCA), and Lo and Zhang (2023) model. The following sections will explore the results from different portfolio sets and provide interpretations of these models, offering a comprehensive perspective on their performance. This analysis will address the research question by evaluating the effectiveness of incorporating ESG factors into financial models for predicting portfolio performance, thus determining their impact on alpha predictions.

6.1 Company Weights Portfolio

The results use stock weights from PGGM portfolios, ensuring each stock's weight reflects its proportion within the original PGGM allocations. This method is relevant because it maintains the original investment strategy and distribution, providing a realistic assessment of the portfolio's performance. By using PGGM's actual weights, the analysis accurately reflects the impact of ESG risk factors on a real-world portfolio, enhancing the realism and accuracy of the findings. Here's the updated table with the provided data, removing the rows not included in the data above:

ESG Factors	Total Portfolio	10% Portfolio	25% Portfolio	40% Portfolio
Gov Score	0.077820	-0.338292	0.239552	0.077039
Mgmt Score	0.056654	-0.342593	0.235049	0.056374
Environment Risk	0.003330	0.053392	-0.040099	0.003417
Carbon Emissions	-0.124437	0.095584	-0.109398	-0.124605
Social Risk	-0.151843	0.370651	-0.301641	-0.151249
Governance Risk	-0.199518	0.407389	-0.334128	-0.198979
Excess Exp	-0.674501	0.473844	-0.578783	-0.674695
Beta	-0.676331	0.477834	-0.579804	-0.676511

Table 6.1: PCA Loadings for Different Portfolio Allocations

PCA Feature Ranking Results

Based on the values in Table 6.1, the analysis reveals several key insights into the most material ESG risk factors across different portfolio allocations.

Governance and management scores emerge as important factors in the total portfolio due to their positive contributions, underscoring the significance of strong governance structures and effective management practices. These elements are vital for long-term financial stability and ethical investment outcomes because they ensure sound decision-making processes and robust risk management.

Beta and excess expenses have the largest negative loadings, which indicates that traditional market risk metrics have the most substantial impact on portfolio performance, primarily in a negative way. These factors reflect the inherent market volatility and operational inefficiencies that can significantly drag down returns if not properly managed. The prominence of these negative factors highlights the critical importance of managing market risk and operational costs to protect the portfolio from adverse outcomes.

Environmental risks, carbon emissions, and social risks, while negatively correlated with portfolio performance, have smaller absolute impacts. This suggests that while poor performance in these areas can detract from returns, their overall influence is less pronounced compared to governance, management quality, and traditional market risks. The smaller absolute values of these factors indicate that they are important but secondary considerations in driving financial performance within this portfolio.

6.1.1 Fama Macbeth Regression Results

The table presents Fama-MacBeth regression results, which highlight the relationship between various ESG-related risk factors and their associated risk premia, standard errors, and Sharpe ratios. The analysis of these results reveals that factors such as governance score and carbon

Risk Factor	Avg Risk Premia	Standard Error	Sharpe Ratio
Gov Score	0.068252	0.001027	66.473359
Carbon Emissions	0.008760	0.000132	66.473177
Constant	1.100233	0.016552	66.472718
High Minus Low (HML)	0.306293	0.091374	3.352088
Small Minus Big (SMB)	0.048533	0.084603	0.573657
Environmental Risk Score	-0.001343	0.000020	-65.599690
Governance Risk Score	-0.041616	0.000626	-66.445840
Management Score	-0.036718	0.000552	-66.468919
Market Beta	-0.024886	0.000374	-66.472903
Excess Expense Score	-0.012126	0.000182	-66.473051
Social Risk Score	-0.057942	0.000871	-66.494785

Table 6.2: Fama-MacBeth Regression Results

emissions stand out due to their strong positive risk premia, coupled with low standard errors and high Sharpe ratios. These findings suggest that firms with high governance scores and effective carbon management tend to offer more consistent and reliable excess returns, indicating a positive relationship between these factors and financial performance.

Conversely, traditional market factors such as High Minus Low (HML) and Small Minus Big (SMB) show moderate to low risk premia, with relatively higher standard errors and lower Sharpe ratios. This indicates that while these factors contribute to returns, their influence is less consistent compared to governance and carbon emissions. The results suggest that the benefits derived from these traditional market factors are more variable and less predictable.

On the other hand, factors such as environmental risk, governance risk, management score, market beta, excess expense score, and social risk exhibit negative risk premia. This indicates that higher levels of these risks are associated with lower returns. The particularly strong negative loadings for social risk, governance risk, and management score emphasize the detrimental impact that poor governance, inadequate management practices, and high social risks can have on portfolio performance. These negative relationships highlight the importance of addressing these risks within an ESG framework to avoid potential adverse effects on financial outcomes.

6.1.2 Alpha Analysis for top-bottom portfolios

The table 6.3 presents normalized total alpha values for different portfolio sizes using various models: FF+ESG, FF3, CAPM, and Lo and Zhang (2023). A key observation from the table is that the FF+ESG model consistently shows less negative normalized alpha values compared to the FF3 and CAPM models across all portfolio sizes. For the most concentrated portfolios, the FF+ESG model performs slightly better, maintaining a stable performance as the portfolio size

	FF+ESG	FF3	CAPM	Lo and Zhang
10% top-bottom Portfolio	-0.018716	-0.020166	-0.020307	-0.000092
25% top-bottom Portfolio	-0.018348	-0.020220	-0.020338	-0.000008
40% top-bottom Portfolio	-0.020204	-0.020366	-0.020505	-0.000008
Whole Portfolio	-0.018889	-0.019676	-0.019837	0.000012

Table 6.3: Normalized Total Alpha for Different Models and Portfolio Sizes

increases. Even for the entire portfolio, the FF+ESG model's normalized total alpha remains slightly better than the other traditional models. In contrast, the Lo and Zhang (2023) model shows near-zero normalized total alpha values across all portfolio sizes, indicating minimal impact compared to the other models.

These observations provide important insights into portfolio performance. The less negative normalized alpha values in the FF+ESG model suggest that integrating ESG factors may enhance portfolio performance by slightly mitigating negative returns. The stark difference between the FF+ESG model and the near-zero values of the Lo and Zhang (2023) model suggests that the latter captures different aspects of risk and return, which are not as influenced by the factors in the FF+ESG, FF3, and CAPM models. The stable performance of the FF+ESG model, particularly in more concentrated portfolios, indicates that ESG integration could help maintain risk-adjusted returns. This effect is particularly evident in portfolios with a higher concentration of ESG characteristics, where top-performing ESG stocks likely help offset the negative impact of the lower-performing ones.

The findings from this table align with the research questions concerning the impact of ESG factors on portfolio performance. The consistent pattern of slightly less negative normalized alpha values in the FF+ESG model across different portfolio sizes suggests that ESG integration may positively influence portfolio outcomes. This indicates that ESG factors might help capture long-term growth opportunities and mitigate risks associated with poor governance and unsustainable practices. The inclusion of ESG considerations in investment strategies appears to have a measurable effect, as reflected in the slightly better performance of the FF+ESG model across various portfolio sizes.

6.1.3 Alpha Distribution Analysis

The whole portfolio's distribution of alpha values derived from three different financial models are presented in the spilted portfolios results are discussed as follows.

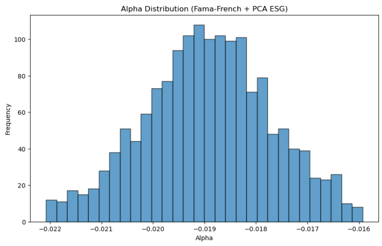


Figure 6.1: Fama-French ESG

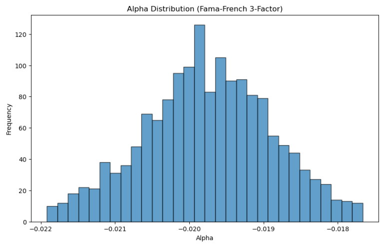


Figure 6.2: Fama-French 3

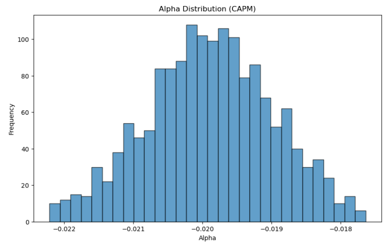


Figure 6.3: CAPM

Fama-French + PCA ESG

The alpha distribution from the Fama-French model augmented with PCA ESG factors shows a relatively symmetric distribution centered around a negative alpha value. The spread of the distribution suggests that integrating ESG factors through PCA results in predominantly negative alphas. This indicates that the investment strategy generally underperformed relative to the benchmark, possibly due to the unique risks or inefficiencies introduced by incorporating ESG considerations.

Fama-French 3-Factor

The alpha distribution for the Fama-French 3-Factor model displays a symmetric, near-normal distribution. The range of alpha values is concentrated around a negative alpha, suggesting consistent underperformance across the portfolio. This distribution implies that the traditional Fama-French 3-Factor model reflects systematic risks that are not fully mitigated, leading to a consistent pattern of negative alpha values.

CAPM

The CAPM model's alpha distribution also exhibits a symmetric pattern similar to the Fama-French 3-Factor model. The concentration of negative alpha values indicates a general underperformance relative to the market. This suggests that the CAPM, which primarily captures market risk, fails to account for other relevant factors, resulting in a consistent negative alpha distribution.

Comparative Analysis

When comparing the three models, all exhibit negative alpha values, indicating underperformance relative to their respective benchmarks. The Fama-French + PCA ESG model shows a relatively symmetric distribution with a peak frequency around a central negative alpha. This suggests that incorporating ESG factors through PCA results in a more concentrated distribution of alpha values, highlighting the unique dynamics and potential challenges associated with

ESG-focused investments. The variability in this model suggests that while ESG integration captures distinct performance characteristics, it may also introduce complexities and additional risks.

In contrast, the Fama-French 3-Factor and CAPM models display narrower and more symmetric distributions of negative alpha values. The distributions of these models are centered around slightly less negative alpha values, indicating a more consistent pattern of underperformance. The similarity in the alpha distributions of these two models implies that the market, size, and value factors in the Fama-French 3-Factor model, as well as the market risk factor in the CAPM model, contribute similarly to the observed underperformance. This comparison suggests that while traditional models provide a more stable performance, they still struggle to achieve positive alpha, possibly due to their inability to fully capture the complexities of ESG-related risks.

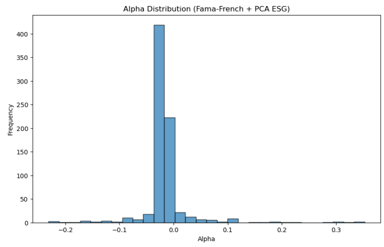
These findings highlight the challenges of achieving positive alpha in ESG investing. The negative alpha values indicate underperformance relative to benchmarks, potentially due to market inefficiencies, the added complexities of ESG considerations, and the limitations of traditional financial models in fully addressing ESG-related risks and returns.

The concentration and symmetry of alpha values in the Fama-French 3-Factor and CAPM models suggest that traditional factors, such as market, size, and value, as well as market risk alone, contribute to consistent but negative performance. This underscores the need for enhanced models that can better account for the multifaceted nature of ESG factors.

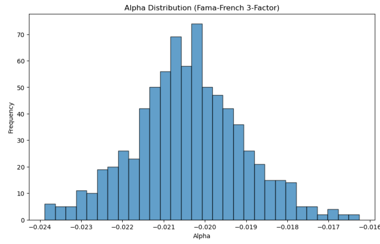
These insights direct attention to the complexities of ESG investing and the importance of developing more sophisticated and comprehensive models that can accurately capture ESG-related risks and opportunities. Moreover, the consistent underperformance across all models relative to benchmarks suggests that ESG investments might require a more nuanced approach and longer time horizons to realize their full potential. This analysis aligns with the broader research question regarding the impact of ESG factors on portfolio performance, highlighting the evolving and intricate nature of integrating ESG considerations into investment strategies.

Alpha Distribution Analysis for Top-Bottom Portfolios

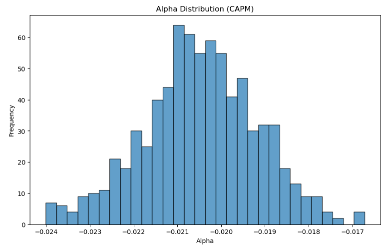
The alpha distribution results offer valuable insights into the performance of different models across various portfolio sizes. For the 10% long/short portfolio, the FF+ESG model (Figure 5.4a) exhibits a very tight distribution of alphas around a central peak, with most alpha values clustered close to zero. This suggests that the FF+ESG model generates more stable and less extreme alpha outcomes compared to the FF3 (Figure 5.4b) and CAPM (Figure 5.4c) models, which display more spread out distributions with peaks around more negative values. The



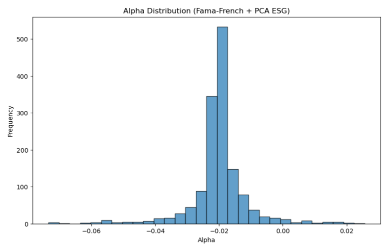
(a) Fama-French ESG ± 10



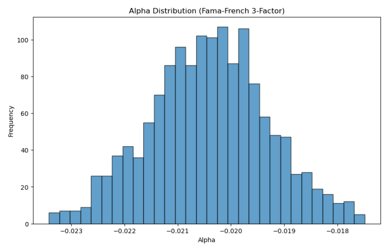
(b) Fama-French ± 10



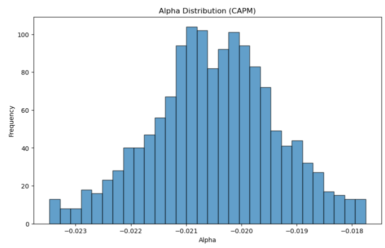
(c) CAPM ± 10



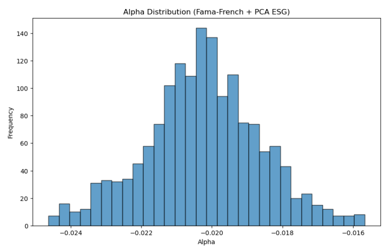
(d) Fama-French ESG ± 25



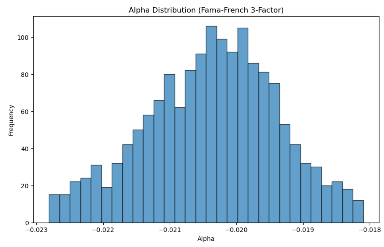
(e) Fama-French ± 25



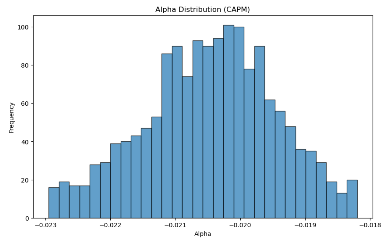
(f) CAPM ± 25



(g) Fama-French ESG ± 40



(h) Fama-French ± 40



(i) CAPM ± 40

Figure 6.4: Comparison of Fama-French and CAPM Models with ESG Considerations

concentration of alpha values near zero in the FF+ESG model indicates that incorporating ESG factors may lead to less volatile performance.

In the 25% long/short portfolio, the FF+ESG model (Figure 5.4d) continues to show a tight distribution of alpha values, although with a slightly broader range compared to the 10% portfolio. The FF3 (Figure 5.4e) and CAPM (Figure 5.4f) models, on the other hand, maintain broader and more negative distributions. This continued pattern suggests that the FF+ESG model provides more stable performance even as the portfolio size increases, with alpha values remaining closer to zero.

For the 40% long/short portfolio, the FF+ESG model (Figure 5.4g) shows a further broadening of the alpha distribution, yet it still maintains a higher frequency of alphas closer to zero compared to the FF3 (Figure 5.4h) and CAPM (Figure 5.4i) models. The distributions for the FF3 and CAPM models remain consistent with their performance in the smaller portfolios, displaying broader ranges and more negative peaks. This suggests that, across all portfolio sizes, the FF+ESG model tends to produce alpha distributions that are less extreme and more concentrated around neutral or slightly negative values.

Factors Influencing the Alpha Distribution

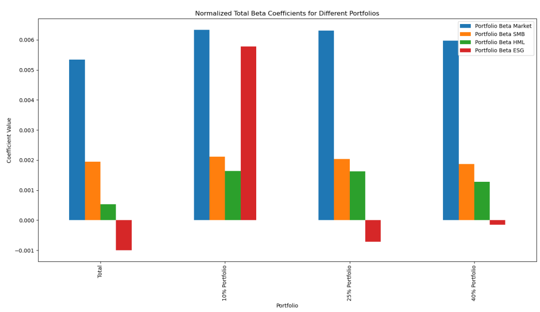
The distinct distribution of the FF+ESG model can be attributed to the integration of ESG factors, which likely capture additional dimensions of risk and return not accounted for by traditional financial models. Companies with strong ESG practices, often large and well-established, typically exhibit more stable financial performance. This stability translates into more concentrated alpha distributions with less extreme negative values in the FF+ESG model.

In the 10% long/short portfolio, the better alpha values in the FF+ESG model could be due to the presence of firms with strong ESG performance, which tend to be larger and more operationally efficient. These firms may generate more consistent returns, which results in less negative alphas. Conversely, the bottom 10% of ESG performers might include firms that are financially strong despite poor ESG scores, contributing to less extreme negative alpha values.

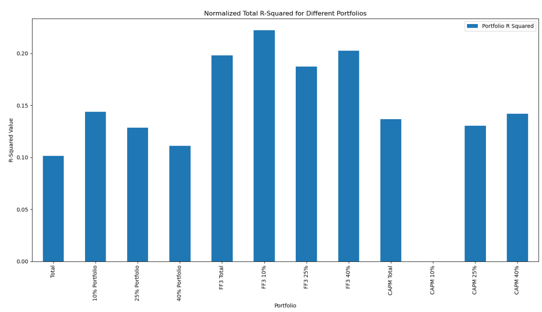
The similarity in alpha distributions between the FF3 and CAPM models suggests that traditional market, size, and value factors, along with market risk alone, affect their performance in similar ways. These models, which primarily capture systematic risks, do not fully reflect the nuances introduced by ESG factors, leading to more consistent but broader distributions of negative alpha values.

The variation in alpha distributions across different portfolio sizes is also influenced by the concentration of stocks with varying ESG performance. In smaller portfolios, the impact of high-performing ESG stocks is more pronounced, leading to more stable alpha values. As the portfolio size increases, the inclusion of a wider range of stocks with diverse ESG characteristics dilutes this effect but still highlights the stabilizing benefits of ESG integration.

6.1.4 Evaluation of the Linear Models



(a) Beta coefficients by Portfolio



(b) R-squared Values by Portfolio

Figure 6.5: Comparison of Random Forest Importance Scores and R-squared Values by Portfolio

The beta coefficients and R-squared values in Figure 6.5 are derived from the Capital Asset

Pricing Model (CAPM) and the Fama-French three-factor model (FF3) applied to different portfolios. Beta coefficients indicate the sensitivity of portfolio returns to various risk factors, while R-squared values measure the proportion of variance in returns explained by the model. The R-squared values show that the FF3 model explains more of the variance in portfolio returns than the CAPM model, though the values are still modest, indicating that both models have limitations in fully capturing portfolio performance.

The beta coefficients reveal that market beta has the most significant positive impact on portfolio returns, while size (SMB) and value (HML) factors contribute less. The ESG beta shows negative coefficients across all portfolios, suggesting a negative sensitivity of returns to ESG factors. These results highlight the need for improved models to better capture the complexities of portfolio returns.

6.1.5 Random Forest Model for Improved Analysis

Given the limitations of the linear models, a Random Forest (RF) model was employed to re-analyze the same set of portfolios. The RF model, a non-linear method, is capable of capturing complex interactions between variables, providing a more flexible framework for modeling portfolio returns. The results from the RF model indicate an enhanced ability to explain portfolio performance compared to linear models.

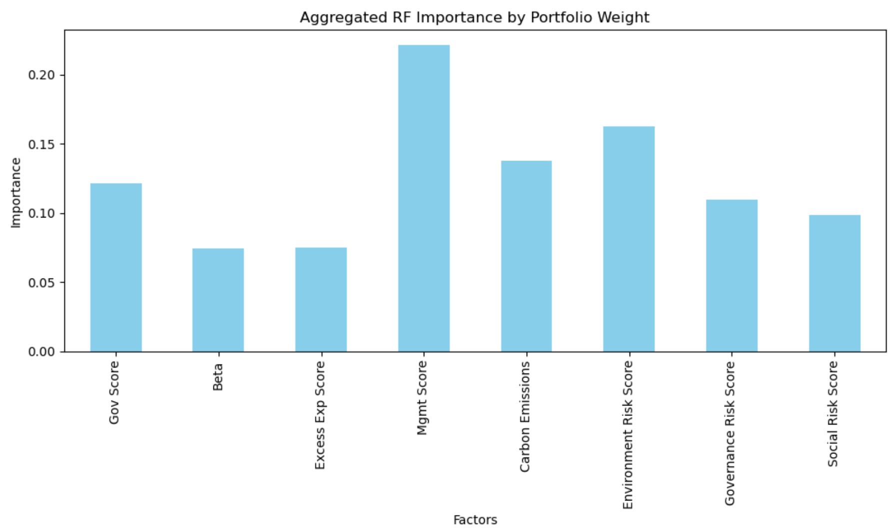


Figure 6.6: Random Forest Importance

The importance scores from the RF model (Figure 6.6) reveal that "Management Score" and "Environment Risk Score" are the most influential factors, with "Governance Score" also showing significant importance. Traditional financial factors such as "Beta" and "Excess Expense Score" are less influential in the RF model, indicating that the non-linear approach captures the importance of ESG factors more effectively than linear models. The consistently higher importance scores for ESG-related factors suggest that the RF model better captures the complexities and non-linear relationships inherent in the data.

Comparing the RF model results with those from the linear models highlights a significant improvement in understanding the drivers of portfolio performance. The RF model not only explains a larger portion of the variance in returns but also emphasizes the critical role of ESG factors, particularly management and environmental risks. This comparison indicates that while linear models provide a basic understanding, they fail to fully capture the dynamics of portfolio performance. The use of advanced non-linear models like Random Forests offers a more accurate and comprehensive analysis.

6.2 Weighted Treynor-Black Portfolios

The Treynor-Black portfolio differs from a typical company portfolio in its construction and objectives. While a company portfolio often assigns weights based on market capitalization, adjusted according to investment strategy, the Treynor-Black portfolio assigns weights using the inverse cumulative distribution function of ESG score rankings, favoring stocks with higher ESG scores. This approach inherently gives higher weights to better-performing ESG stocks. Additionally, the Treynor-Black portfolio focuses on optimizing alpha and managing betas, specifically aiming to achieve excess returns while controlling exposure to systematic risk factors. The method involves combining an active ESG portfolio with a passive market index to balance the potential benefits of high ESG score stocks with the stability of a market index, resulting in an optimized risk-return profile.

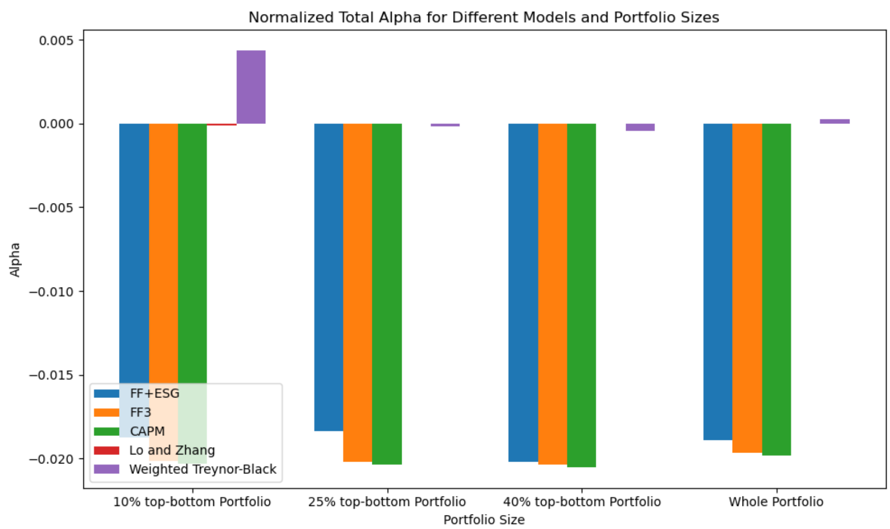


Figure 6.7: Total Alpha for Different Models and Portfolio Sizes

The Weighted Treynor-Black Portfolio alphas are close to zero, similar to those of the Lo and Zhang (2023) model, and less negative than those from the FF+ESG, FF3, and CAPM models. This similarity likely results from the Treynor-Black model's focus on minimizing idiosyncratic risk by blending an active portfolio with a market portfolio, leading to alphas that align closely with market returns. The Lo and Zhang (2023) model, which captures specific market inefficiencies, also produces near-zero alphas, indicating limited deviation from expected returns.

Both the Treynor-Black and Lo and Zhang (2023) models appear to limit exposure to the risk factors that contribute to the more negative alphas observed in the other models. By avoiding overexposure to high-beta or volatile stocks, these models achieve alphas near zero, reflecting efficient risk management and diversification. The near-zero alphas suggest that these models are well-hedged against systematic risks and align closely with market expectations.

7

Conclusion

This chapter synthesizes the answers to research questions and contributions of the thesis, reflecting on the integration of Environmental, Social, and Governance (ESG) factors into financial models. It discusses the practical and academic implications of the research, acknowledges the study's limitations, and outlines potential directions for future research. The chapter also highlights how the research aligns with the objectives of the Management of Technology program, emphasizing the importance of technological innovation in enhancing sustainable investment strategies.

7.1 Addressing the Research Questions

7.1.1 Sub-Questions

What are the most material ESG risk factors?

Identifying the most material ESG risk factors is crucial for investors seeking to enhance portfolio performance while managing risks associated with environmental, social, and governance issues. To address this, Principal Component Analysis (PCA) and Fama-MacBeth regression were employed to analyze and rank these factors based on their impact across different portfolio allocations.

PCA is a statistical technique that reduces the dimensionality of a dataset by identifying the most influential variables, revealing the underlying structure of ESG factors. The analysis shows that ”Governance Score” and ”Management Score” are critical in driving positive portfolio outcomes, contributing positively to overall stability. In contrast, traditional market risk metrics such as ”Beta” and ”Excess Expenses” have substantial negative loadings, indicating their significant detrimental impact on portfolio performance.

Fama-MacBeth regression complements this analysis by estimating the risk premia and Sharpe ratios associated with ESG factors over time. The results emphasize ”Governance Score” and ”Carbon Emissions” as key factors, both with high positive risk premia and low standard errors, suggesting that firms excelling in governance and carbon management are more likely to achieve stable and reliable excess returns. Conversely, factors like ”Environmental Risk,” ”Governance Risk,” ”Management Score,” and ”Social Risk” exhibit negative risk premia, indicating that higher levels of these risks are associated with lower returns.

Together, these analyses underscore the critical role of governance and ESG management in mitigating risks and enhancing financial performance. The findings suggest that integrating robust ESG criteria into investment strategies is essential for achieving long-term value creation.

How can the impact of ESG risk factors be quantified in a portfolio?

The impact of ESG risk factors in a portfolio can be quantified using a comprehensive analysis pipeline that incorporates data from Sustainalytics and BlackRock, along with portfolio data from PGGM. This research employs four financial models to compare alpha predictions and evaluate the influence of ESG factors: the Capital Asset Pricing Model (CAPM), the traditional Fama-French three-factor model (FF3), a Fama-French model enhanced with ESG risk factors through PCA and Fama-MacBeth regression (FF+ESG), the Lo and Zhang (2023) model, and a non-linear random forest model.

Portfolio Construction

The study uses stock weights from the PGGM portfolio, ensuring each stock’s weight reflects its proportion in the original PGGM allocation. This method maintains the original investment strategy and allocation, providing a realistic assessment of portfolio performance. By using PGGM’s actual weights, the analysis accurately reflects the impact of ESG risk factors on real-world portfolios.

The Treynor-Black portfolio allocates weights using the inverse cumulative distribution function of ESG score rankings, favoring stocks with higher ESG scores. This approach optimizes alpha while managing beta, aiming to achieve excess returns while controlling for exposure to systemic risk factors. The results indicate that the weighted Treynor-Black portfolio’s alpha is close to zero and shows fewer negative values compared to other models, reflecting the effectiveness of its optimization strategy.

Alpha Analysis of Top and Bottom Portfolios

Alpha analysis shows that the FF+ESG model exhibits less negative normalized alpha values across all portfolio sizes, suggesting that integrating ESG factors can enhance portfolio performance by reducing negative returns. In contrast, the Lo and Zhang (2023) model shows near-zero normalized alpha values across all portfolio sizes, indicating minimal impact. These findings suggest that ESG integration can lead to better risk-adjusted returns, particularly in concentrated portfolios with more ESG features.

Evaluation of Models and Improved Analysis

The beta coefficients and R-squared values of linear models, including CAPM and the Fama-French three-factor model, demonstrate limited explanatory power for portfolio returns, underscoring the need for alternative approaches to better capture the complexity of portfolio dynamics. The Random Forest (RF) model, reanalyzing the same portfolios, shows significant improvement by effectively capturing complex interactions between variables. The RF model results indicate that while traditional financial factors like ”Beta” and ”Excess Expense Score” are still relevant, ESG factors, particularly ”Management Score” and ”Environment Risk Score,” emerge as the most influential determinants of portfolio performance, reflecting the model’s enhanced ability to account for non-linear relationships in the data.

What is the relationship between ESG risk factors and the risk and return profiles of investment portfolios?

The analysis indicates a significant relationship between ESG risk factors and the risk and return profiles of investment portfolios. Portfolios that integrate ESG factors, such as those employing the FF+ESG model, exhibit less negative alpha values, suggesting that ESG factors contribute to risk mitigation and potentially enhanced returns. The examination of normalized total alpha values across various portfolio sizes supports this finding, demonstrating that portfolios with higher concentrations of ESG characteristics tend to perform more consistently. This relationship underscores the critical role of ESG risk factors, including management quality, governance practices, and environmental risks, in influencing the risk and return dynamics of equity investment portfolios.

Specifically, the PCA highlights the importance of governance and management scores across different portfolio allocations. For instance, in the 10% long/short portfolio, the FF+ESG model’s alpha values are closer to zero, indicating that the integration of governance and management quality results in more stable portfolio performance. Compared to traditional models like the Fama-French 3-Factor model and the CAPM, the FF+ESG model consistently shows better performance across various portfolio sizes, with less negative alpha values and higher stability.

Furthermore, the Fama-MacBeth regression results emphasize the significance of governance scores and carbon emissions in delivering reliable excess returns. Notably, the governance score stands out due to its high average risk premia and low standard error, suggesting that companies with strong governance practices are often better managed and more sustainable, thereby achieving higher returns.

In addition, the analysis of the weighted Treynor-Black portfolio reveals alpha values close to zero, similar to those observed in the Lo and Zhang (2023) model, and less negative compared to other models. This similarity likely arises from the optimization strategy of the Treynor-Black model, which aims to minimize idiosyncratic risk and enhance the Sharpe ratio by blending an active portfolio with a market portfolio, thereby aligning closely with expected market returns.

7.1.2 Central Research Question

How do ESG risk factors affect the risk and return dynamics of equity investment portfolios?

The analysis demonstrates that integrating ESG risk factors significantly influences the risk and return dynamics of equity investment portfolios. This effect is evident through multiple dimensions of the research.

Identification of Material ESG Risk Factors:

PCA and Fama-MacBeth regression both highlight the critical importance of specific ESG risk factors. PCA identifies ”Governance Score” and ”Management Score” as the most influential factors across various portfolio allocations, emphasizing the role of strong governance and effective management in driving positive portfolio outcomes. Fama-MacBeth regression further emphasizes the significance of ”Governance Score” and ”Carbon Emissions,” associating these factors with high risk premia and low standard errors. These findings suggest that companies with robust governance and effective carbon management practices are rewarded with higher returns, reflecting a growing investor focus on sustainability and sound management practices.

Quantification of ESG Impact:

The impact of ESG risk factors is quantified through a comprehensive analysis pipeline using data from various portfolios. By comparing the alpha predictions of different financial models—CAPM, FF3, FF+ESG (enhanced with PCA and Fama-MacBeth regression), Lo and

Zhang (2023), and a non-linear random forest model—the research assesses the influence of ESG factors on portfolio performance. The study uses realistic stock weights to maintain practical relevance and employs the Treynor-Black portfolio construction to optimize alpha and manage beta, demonstrating fewer negative alpha values compared to other models.

Evaluation of Models and Performance:

Alpha analysis indicates that the FF+ESG model exhibits less negative normalized alpha values across all portfolio sizes, suggesting that integrating ESG factors can improve portfolio performance by mitigating negative returns. In contrast, the Lo and Zhang (2023) model shows near-zero normalized alpha values, indicating stable performance with minimal impact. Furthermore, the random forest model captures complex interactions between variables, offering a more flexible and accurate framework for modeling portfolio returns and showing significant improvement over linear models like CAPM and FF3.

Relationship Between ESG Risk Factors and Portfolio Dynamics:

The relationship between ESG risk factors and the risk and return profiles of investment portfolios is further elucidated by examining normalized total alpha values. Portfolios with higher concentrations of ESG characteristics consistently perform better, underscoring the critical role of ESG risk factors, including governance practices, management quality, and environmental risks, in determining the risk and return dynamics of equity investment portfolios. Specifically, the FF+ESG model's superior performance across various portfolio sizes indicates that ESG factors contribute to more stable and positive portfolio performance compared to traditional models.

In conclusion, the integration of ESG risk factors into investment strategies enhances the risk-adjusted returns of equity portfolios. This is achieved by capturing additional dimensions of risk and return not addressed by traditional financial models, thereby supporting the notion that ESG integration is not only socially responsible but also financially prudent.

7.2 Reflection

Initially, I anticipated that integrating ESG risk factors into traditional financial models would directly enhance portfolio performance. However, the research process revealed complexities and nuances that I had not foreseen. A significant challenge was the inconsistency of ESG data, necessitating extensive data cleaning and validation. Adjusting the research plan to include PCA and Fama-MacBeth regression was essential to ensure the robustness of the study, significantly improving its accuracy.

Reflecting on this process, I realize that incorporating real-time data and longitudinal studies could have provided a more dynamic understanding of ESG impacts over time. Expanding the range of ESG factors considered and employing different modeling techniques earlier in the study might have uncovered additional insights.

Throughout the research, I gained a deep understanding of advanced quantitative methods and their application in financial modeling. This included constructing a time-series database, recognizing the complexity and non-linear nature of ESG impacts, and analyzing model performance. The process of improving experimental design, such as incorporating random forest and Fama-MacBeth regression methods, provided a renewed perspective on ESG integration in asset pricing models, ultimately enriching the existing literature and offering practical guidance for investors to quantify ESG risks and enhance portfolio resilience.

From a practical standpoint, the research confirms the clear benefits of integrating ESG factors into investment strategies. The study's findings underscore the value of continued exploration into ESG risk integration, demonstrating that it not only enhances portfolio resilience but also aligns financial goals with societal values. This is particularly pertinent as investors, institutions, and policymakers grapple with critical global challenges such as climate change, social inequality, and corporate governance.

The societal implications of this research are significant. As global awareness of sustainability issues intensifies, the demand for investment strategies that transcend the pursuit of financial returns is increasing. This research substantiates the role of ESG integration in responsible investing, potentially motivating a larger segment of investors to adopt sustainable practices.

From an academic standpoint, this study contributes meaningfully to the discourse in sustainable finance by addressing gaps related to ESG data inconsistencies and advancing the use of quantitative methods, culminating in the development of an ESG-integrated multi-factor model. This model, together with the application of PCA and Fama-MacBeth regression, offers a novel approach to assessing ESG impacts and sets a precedent for methodological innovation in future research.

This research process has strengthened my independent research capabilities. Through extensive literature review, I identified suitable research methods and applied existing methodologies flexibly to new datasets. I spent considerable time learning new data platforms and understanding the scoring standards of ESG rating agencies. Overcoming these obstacles required perseverance, which enhanced my resilience. This experience has also clarified my future aspirations, reinforcing my interest in continuing research in sustainable finance.

7.3 Contribution of the Thesis

This research makes several important contributions to the field from both academic and practical perspectives.

7.3.1 Academic Contributions

Firstly, this study adopts a quantitative framework for integrating ESG risk factors into traditional financial models, offering new insights into how ESG considerations can influence risk-adjusted returns. The quantitative framework developed by Lo and Zhang (2023), along with an ESG-integrated Fama-French multifactor model, is evaluated and compared to traditional models such as the Fama-French three-factor model and the Capital Asset Pricing Model (CAPM). The findings indicate that the ESG-integrated model slightly enhances portfolio performance by reducing negative excess returns compared to traditional asset pricing models.

Secondly, the application of PCA and Fama-MacBeth regression to identify key ESG factors—such as the ESG Risk Score, Management Gap Score, and Governance Score—enhances the theoretical understanding of the most influential ESG elements. This method offers a detailed perspective on the connection between ESG factors and financial performance, contributing to the existing literature on ESG integration in asset pricing models.

7.3.2 Practical Contributions

From a practical standpoint, the research demonstrates the clear benefits of integrating ESG factors into investment strategies. The study's findings highlight the importance of effective management and strong governance structures in improving financial performance, reinforcing the value of ESG integration for investors. By identifying specific ESG factors that are crucial for enhancing portfolio performance, the research provides investors with actionable insights.

Furthermore, the comparative analysis of ESG-integrated models and traditional models offers practical guidance for asset managers seeking to improve risk-adjusted returns through ESG integration. The evidence that ESG models can reduce negative excess returns suggests that incorporating ESG considerations can lead to more resilient investment portfolios. Additionally, this research tests the latest framework using a real investment portfolio and builds a pipeline for ongoing iterative research, contributing to practical advancements in the field.

7.4 Limitations

While this research provides significant insights, it is important to acknowledge its limitations. The study's time frame was limited to a four-month period, which may not fully capture the long-term impacts of ESG integration and the volatility may influnece the model results. However, I have built up a pipeline from data loading, preprocessing, model building, and testing, results visualization. So the follow-up research could be easily conducted to adopt wider time span of the data. And for this research, I choose the daily level data for a portfolio contains 2,000 stocks, which may minimize the influence of limited data input.

Another limit comes the availability and quality of ESG data varied across sources, which could introduce biases or inconsistencies. The reliance on secondary ESG risk data sources from Sustainanlytics also include bias, as the ESG risk factors may be context dependent. Here, the ESG risk data is exclusive to the company database and there are also other rating agencies ESG data which may contain less ESG risk factors but with the prebuilt pipeline I could further inspect the ESG risk factors impact on investment easily.

The third limitation is that linear asset pricing models capture only a limited variance of contemporary investment portfolios. In contrast, non-linear models, such as random forests, perform better than traditional models. However, the interpretability of these non-linear models is often a trade-off, as research may not fully recognize the specific relationships between factors.

7.5 Future Research

Future research could address current limitations by expanding the time horizon to include multiple years, providing a more comprehensive view of the long-term effects of ESG investing. Additionally, incorporating a broader range of geographical regions and industry sectors could offer more generalized insights into ESG impacts. Examining the evolving regulatory landscape and its influence on ESG reporting and performance would also be valuable.

ESG should be viewed through a long-term value lens, allowing for the study of value-creating issues beyond ESG categories. This perspective highlights that intangible assets, such as human, organizational, or innovation capital, may sometimes be more relevant than ESG for certain research questions. Research should focus on specific ESG dimensions rather than aggregate ESG scores. For instance, environmental performance should be measured using relevant components rather than broad ESG ratings. Titles and abstracts of research papers should clearly reflect the specific ESG dimensions addressed in the study.

ESG variables should not be assumed to be linearly beneficial; insignificant or non-linear results can provide valuable insights. Recognizing the complexity and non-linear nature of ESG impacts is crucial for advancing knowledge in this field. High-quality qualitative measures may predict long-term returns better than mere quantity-based measures. Incorporating qualitative assessments can capture aspects of ESG not reflected in quantitative data, providing a more holistic understanding of ESG impacts.

Further studies could investigate the specific mechanisms through which ESG factors influence financial performance. For example, examining how different ESG components interact with macroeconomic indicators or how investor sentiment towards ESG evolves over time could provide deeper insights. Advanced modeling techniques, such as machine learning, could be employed to uncover hidden patterns and improve prediction accuracy. Additionally, exploring the interactions between ESG and other drivers of long-term value is important. Research should investigate the relationship between ESG and other intangible assets, such as innovation, to determine whether ESG complements or substitutes other value drivers.

7.6 Alignment with Management of Technology

The research findings of this thesis demonstrate the integration of ESG risk factors into financial models, illustrating how technological innovation can enhance investment strategies and provide a strategic advantage in competitive, technology-driven environments. This study applies the analytical and innovative capabilities fostered in the Management of Technology program, particularly those developed in the Financial Management and Research Methods courses, which laid the foundation for my understanding of finance and independent research. Additionally, I utilized machine learning and data processing skills acquired from elective courses such as Spatial Data Science and AI Fundamentals Specialization.

This research provides a quantitative framework for ESG assessment, innovatively integrating ESG risk factors into traditional investment strategies. This approach aligns with the strategic trend towards sustainable investment and equips me to address the complexities of technological, economic, and social challenges. Moreover, it has enhanced my ability to quickly learn and apply new technologies and consider their applications in various fields. For instance, applying machine learning and artificial intelligence to finance and sustainable investment will be a focus of my future research, and I will continue to build on this knowledge.

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A

Source Code

A.1 Calculate Aggregated ESG Score Using PCA

```
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA

def calculate_aggregated_esg_score(data):
    """
    Calculate the aggregated ESG score using PCA.

    Parameters:
    data (pd.DataFrame): The input dataframe containing the necessary
        columns.

    Returns:
    pd.DataFrame: The dataframe with the added aggregated ESG score.
    """
    columns_of_interest = ['Gov_Score', 'Beta', 'Excess_Exp_Score', '
        Mgmt_Score',
                           'Carbon_Emissions', 'Environment_Risk_score',
                           'Governance_Risk_score', 'Social_Risk_score']

    data_selected = data[columns_of_interest]
    scaler = StandardScaler()
    data_normalized = scaler.fit_transform(data_selected)

    pca = PCA(n_components=1)
```

```
    pca_scores = pca.fit_transform(data_normalized)

    data['PCA_ESG_Score'] = pca_scores

    explained_variance = pca.explained_variance_ratio_[0]
    print(f"Explained␣Variance␣Ratio␣by␣the␣first␣component:␣{explained_variance}")

    return data
```

A.2 Fama Macbeth Regression

```
import pandas as pd
from sklearn.preprocessing import StandardScaler

def fama_macbeth_regression(data, risk_factors):
    data_copy = data.copy()
    scaler = StandardScaler()
    data_copy[risk_factors] = scaler.fit_transform(data_copy[risk_factors])

    data_copy['Excess_Return'] = data_copy['Return'] - data_copy['RF']
    time_series_results = {}

    for cusip in data_copy['CUSIP'].unique():
        stock_data = data_copy[data_copy['CUSIP'] == cusip]
        if len(stock_data) > 1:
            X = stock_data[risk_factors]
            X = sm.add_constant(X)
            y = stock_data['Excess_Return']
            model = sm.OLS(y, X).fit()
            time_series_results[cusip] = model.params

    betas = pd.DataFrame.from_dict(time_series_results, orient='index')

    risk_factors_with_const = ['const'] + risk_factors
    if len(betas.columns) != len(risk_factors_with_const):
        print(f"Expected␣{len(risk_factors_with_const)}␣columns␣but␣got␣{len(betas.columns)}.␣Adjusting␣the␣column␣names.")
        print("Available␣columns␣in␣betas:", betas.columns)
        print("Expected␣columns:", risk_factors_with_const)

    betas.columns = risk_factors_with_const[:len(betas.columns)]

```

```
    cross_sectional_results = []

    for date in data_copy['Date'].unique():
        date_data = data_copy[data_copy['Date'] == date]
        date_betas = betas.loc[date_data['CUSIP']].dropna()
        date_excess_returns = date_data.set_index('CUSIP')['Excess_Return'
            ]

        common_index = date_betas.index.intersection(date_excess_returns.
            index)
        date_betas = date_betas.loc[common_index]
        date_excess_returns = date_excess_returns.loc[common_index]

        if len(date_betas) > 1:
            X = date_betas
            y = date_excess_returns
            model = sm.OLS(y, X).fit()
            cross_sectional_results.append(model.params)

    cross_sectional_results_df = pd.DataFrame(cross_sectional_results)

    avg_risk_premia = cross_sectional_results_df.mean()
    std_errors = cross_sectional_results_df.std() / (len(
        cross_sectional_results_df) ** 0.5)

    results = pd.DataFrame({
        'Avg_Risk_Premia': avg_risk_premia,
        'Standard_Error': std_errors
    })

    return results

risk_factors = ['SMB', 'HML', 'Beta', 'Gov_Score', 'Excess_Exp_Score', '
    Mgmt_Score',
                'Carbon_Emissions', 'Environment_Risk_score',
                'Governance_Risk_score', 'Social_Risk_score']

results = fama_macbeth_regression(merged_df, risk_factors)
```

A.3 Split the Portfolios into 3 Sub-Portfolios Based on PCA Processed ESG Score

```
import pandas as pd
```

```

def create_quantile_portfolios_and_merge_weights(data_df):
    data_df = data_df.sort_values(by='PCA_ESG_Score', ascending=False).reset_index(drop=True)

    num_stocks = len(data_df)
    decile_size = num_stocks // 10
    quartile_size = num_stocks // 4
    four_deciles_size = 4 * decile_size

    pf_10_long = data_df.head(decile_size)
    pf_10_short = data_df.tail(decile_size)

    pf_25_long = data_df.head(quartile_size)
    pf_25_short = data_df.tail(quartile_size)

    pf_40_long = data_df.head(four_deciles_size)
    pf_40_short = data_df.tail(four_deciles_size)

    portfolio_10 = pd.concat([pf_10_long, pf_10_short])
    portfolio_25 = pd.concat([pf_25_long, pf_25_short])
    portfolio_40 = pd.concat([pf_40_long, pf_40_short])

    return portfolio_10, portfolio_25, portfolio_40

portfolio_10, portfolio_25, portfolio_40 = create_quantile_portfolios_and_merge_weights(merged_df)
```

A.4 Asset Pricing Models: FF3, CAPM, FF4(ESG)

```
import pandas as pd
from sklearn.decomposition import PCA
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import numpy as np
import matplotlib.pyplot as plt
import xgboost as xgb

def handle_missing_values(df, columns):
    df[columns] = df[columns].apply(pd.to_numeric, errors='coerce')
    df[columns] = df[columns].interpolate(method='linear', limit_direction='forward', axis=0).fillna(method='bfill')
    return df
```

```python

def calculate_aggregated_esg_score(data):
    columns_of_interest = ['Gov_Score', 'Beta', 'Excess_Exp_Score', 'Mgmt_Score',
                           'Carbon_Emissions', 'Environment_Risk_score',
                           'Governance_Risk_score', 'Social_Risk_score']

    data_selected = data[columns_of_interest]
    scaler = StandardScaler()
    data_normalized = scaler.fit_transform(data_selected)
    pca = PCA(n_components=1)
    pca_scores = pca.fit_transform(data_normalized)
    data['PCA_ESG_Score'] = pca_scores
    explained_variance = pca.explained_variance_ratio_[0]
    print(f"Explained Variance Ratio by the first component: {explained_variance}")

    # update the data with the normalized values
    data[columns_of_interest] = data_normalized

    return data

def run_regression(data, factors, factor_columns):
    results_df = pd.DataFrame(columns=[
        'CUSIP', 'Alpha', 'Beta_Market', 'Beta_SMB', 'Beta_HML', 'Beta_ESG', 'R_squared',
        'P_value_Alpha', 'P_value_Market', 'P_value_SMB', 'P_value_HML', 'P_value_ESG',
        'Portfolio Weight', 'PCA_ESG_Score', 'RF_Importance'
    ], index=data['Security Description'].unique())

    for stock in data['Security Description'].unique():
        stock_data = data[data['Security Description'] == stock].dropna(subset=['Excess_Return'] + factor_columns.tolist())
        if len(stock_data) < 2:
            continue

        model = sm.OLS(stock_data['Excess_Return'], factors.loc[stock_data.index])
        result = model.fit()

        results_df.loc[stock] = [
            stock_data['CUSIP'].iloc[0],
            result.params.get('const', np.nan),
            result.params.get('Excess_Market_Return', np.nan),
```

```
                result.params.get('SMB', np.nan),
                result.params.get('HML', np.nan),
                result.params.get('PCA_ESG_Score', np.nan),
                result.rsquared,
                result.pvalues.get('const', np.nan),
                result.pvalues.get('Excess_Market_Return', np.nan),
                result.pvalues.get('SMB', np.nan),
                result.pvalues.get('HML', np.nan),
                result.pvalues.get('PCA_ESG_Score', np.nan),
                stock_data['Portfolio Weight'].iloc[0],
                stock_data['PCA_ESG_Score'].iloc[0],
                np.nan  # Placeholder for RF_Importance
            ]

    return results_df

def run_fama_french_regression_with_pca(data):
    data['Excess_Market_Return'] = data['FTSE_Daily_Return'] - data['RF']
    factors = sm.add_constant(data[['Excess_Market_Return', 'SMB', 'HML', 'PCA_ESG_Score']])
    return run_regression(data, factors, factors.columns[1:])

def run_fama_french_3f_regression(data):
    data['Excess_Market_Return'] = data['FTSE_Daily_Return'] - data['RF']
    factors = sm.add_constant(data[['Excess_Market_Return', 'SMB', 'HML']])
    return run_regression(data, factors, factors.columns[1:])

def run_capm_regression(data):
    data['Excess_Market_Return'] = data['FTSE_Daily_Return'] - data['RF']
    factors = sm.add_constant(data[['Excess_Market_Return']])
    return run_regression(data, factors, factors.columns[1:])

def run_rf_model(data, factor_columns):
    results = []
    for stock in data['Security Description'].unique():
        stock_data = data[data['Security Description'] == stock].dropna(subset=['Excess_Return'] + factor_columns)
        if len(stock_data) < 2:
            continue
        X_train, X_test, y_train, y_test = train_test_split(stock_data[factor_columns], stock_data['Excess_Return'], test_size=0.2, random_state=42)
        rf_model = RandomForestRegressor(n_estimators=100, random_state=42).fit(X_train, y_train)
```

```
        results.append((stock, rf_model.feature_importances_))
    return results

def filter_alpha_percentiles(results_df, lower_percentile=0.03, upper_percentile=0.97):
    lower_bound = results_df['Alpha'].quantile(lower_percentile)
    upper_bound = results_df['Alpha'].quantile(upper_percentile)
    return results_df[(results_df['Alpha'] >= lower_bound) & (results_df['Alpha'] <= upper_bound)]

def plot_alpha_distribution(results_df, title):
    plt.figure(figsize=(10, 6))
    plt.hist(results_df['Alpha'].dropna(), bins=30, edgecolor='k', alpha=0.7)
    plt.title(title)
    plt.xlabel('Alpha')
    plt.ylabel('Frequency')
    plt.show()

def calculate_total_alpha(df, alpha_column):
    total_alpha = df[alpha_column].sum()
    total_portfolio_weight = df['Portfolio Weight'].sum()
    df['Normalized Weight'] = df['Portfolio Weight'] / total_portfolio_weight
    df['Alpha_Contribution'] = df['Normalized Weight'] * df[alpha_column]
    total_alpha_normalized = df['Alpha_Contribution'].sum()
    return total_alpha_normalized, df

def add_rf_importances_to_results(results_df, rf_results, factor_columns):
    for stock, importances in rf_results:
        if stock in results_df.index:
            for i, factor in enumerate(factor_columns):
                results_df.at[stock, f'RF_Importance_{factor}'] = importances[i]

def run_xgboost_model(data, factor_columns, target_column='Excess_Return'):
    results = []
    for stock in data['Security Description'].unique():
        stock_data = data[data['Security Description'] == stock].dropna(subset=[target_column] + factor_columns)
        if len(stock_data) < 2:
            continue
        X_train, X_test, y_train, y_test = train_test_split(stock_data[factor_columns], stock_data[target_column], test_size=0.2,
```

```python
            random_state=42)
        xgb_model = xgb.XGBRegressor(n_estimators=100, random_state=42).fit(X_train, y_train)
        results.append((stock, xgb_model.feature_importances_))
    return results

def add_xgb_importances_to_results(results_df, xgb_results, factor_columns):
    for stock, importances in xgb_results:
        if stock in results_df.index:
            for i, factor in enumerate(factor_columns):
                results_df.at[stock, f'XGB_Importance_{factor}'] = importances[i]

def plot_comparison_bar_chart(pca_importances, xgb_importances, feature_names, title):
    plt.figure(figsize=(12, 8))
    bar_width = 0.35
    index = np.arange(len(feature_names))

    plt.bar(index, pca_importances, bar_width, label='PCA Importance')
    plt.bar(index + bar_width, xgb_importances, bar_width, label='XGBoost Importance')

    plt.xlabel('Features')
    plt.ylabel('Importance')
    plt.title(title)
    plt.xticks(index + bar_width / 2, feature_names, rotation=45)
    plt.legend()
    plt.tight_layout()
    plt.show()

def evaluate_residuals(results_df, df_processed):
    residuals = []
    for stock in results_df.index:
        stock_data = df_processed[df_processed['Security Description'] == stock].dropna(subset=['Excess_Return'])
        if len(stock_data) < 2:
            continue
        model = sm.OLS(stock_data['Excess_Return'], sm.add_constant(stock_data[['Excess_Market_Return', 'SMB', 'HML', 'PCA_ESG_Score']]))
        result = model.fit()
        residuals.extend(result.resid)
    return residuals
```

```

def plot_residual_distribution(residuals, title):
    plt.figure(figsize=(10, 6))
    plt.hist(residuals, bins=30, edgecolor='k', alpha=0.7)
    plt.title(title)
    plt.xlabel('Residuals')
    plt.ylabel('Frequency')
    plt.show()

def main(data_weighted):
    # Handle missing values
    columns_to_process = ['Gov_Score', 'Beta', 'Excess_Exp_Score', 'Mgmt_Score',
                          'Carbon_Emissions', 'Environment_Risk_score',
                          'Governance_Risk_score', 'Social_Risk_score']
    # data_weighted = handle_missing_values(data_weighted, columns_to_process)

    # Calculate aggregated ESG score using PCA
    df_processed = calculate_aggregated_esg_score(data_weighted)
    df_processed['Excess_Return'] = df_processed['Return'] - df_processed['RF']

    pca_results = run_fama_french_regression_with_pca(df_processed)
    ff3_results = run_fama_french_3f_regression(df_processed)
    capm_results = run_capm_regression(df_processed)

    feature_names = ['Gov_Score', 'Beta', 'Excess_Exp_Score', 'Mgmt_Score',
                     'Carbon_Emissions', 'Environment_Risk_score',
                     'Governance_Risk_score', 'Social_Risk_score']

    rf_results = run_rf_model(df_processed, feature_names)
    add_rf_importances_to_results(pca_results, rf_results, feature_names)
    add_rf_importances_to_results(ff3_results, rf_results, feature_names[:-1])
    add_rf_importances_to_results(capm_results, rf_results, feature_names[:1])

    xgb_results = run_xgboost_model(df_processed, feature_names)
    add_xgb_importances_to_results(pca_results, xgb_results, feature_names)
    add_xgb_importances_to_results(ff3_results, xgb_results, feature_names[:-1])
    add_xgb_importances_to_results(capm_results, xgb_results,
```

```
        feature_names[:1])

    filtered_pca_results = filter_alpha_percentiles(pca_results)
    filtered_ff3_results = filter_alpha_percentiles(ff3_results)
    filtered_capm_results = filter_alpha_percentiles(capm_results)

    plot_alpha_distribution(filtered_pca_results, 'Alpha Distribution (
        Fama-French + PCA ESG)')
    plot_alpha_distribution(filtered_ff3_results, 'Alpha Distribution (
        Fama-French 3-Factor)')
    plot_alpha_distribution(filtered_capm_results, 'Alpha Distribution (
        CAPM)')

    total_alpha_pca, _ = calculate_total_alpha(filtered_pca_results, '
        Alpha')
    total_alpha_ff3, _ = calculate_total_alpha(filtered_ff3_results, '
        Alpha')
    total_alpha_capm, _ = calculate_total_alpha(filtered_capm_results, '
        Alpha')

    print(f"Total normalized alpha for Fama-French + PCA ESG: {
        total_alpha_pca}")
    print(f"Total normalized alpha for Fama-French 3-Factor: {
        total_alpha_ff3}")
    print(f"Total normalized alpha for CAPM: {total_alpha_capm}")

    return filtered_pca_results, filtered_ff3_results,
        filtered_capm_results, df_processed

# Example usage
# filtered_pca_results, filtered_ff3_results, filtered_capm_results,
    df_processed = main(data_weighted)
```

A.5 Lo and Zhang's Model

```
import numpy as np
import pandas as pd
from scipy.stats import norm

def estimate_parameters(merged_df):
    merged_df['Alpha'] = pd.to_numeric(merged_df['Alpha'], errors='coerce'
        )
    merged_df['PCA_ESG_Score'] = pd.to_numeric(merged_df['PCA_ESG_Score'],
         errors='coerce')
```

```

    if merged_df['Alpha'].isnull().any() or merged_df['PCA_ESG_Score'].isnull().any():
        raise ValueError("Input data contains NaN values.")
    if not np.isfinite(merged_df['Alpha']).all() or not np.isfinite(merged_df['PCA_ESG_Score']).all():
        raise ValueError("Input data contains infinite values.")

    rho = np.corrcoef(merged_df['Alpha'], merged_df['PCA_ESG_Score'])[0, 1]
    sigma_alpha = merged_df['Alpha'].std()

    return rho, sigma_alpha

def simulate_order_statistics(N, num_simulations=10000):
    simulations = np.sort(np.random.randn(num_simulations, N), axis=1)
    means = np.mean(simulations, axis=0)
    variances = np.var(simulations, axis=0)
    covariances = np.cov(simulations, rowvar=False)

    return means, variances, covariances

def compute_expected_alpha(rho, sigma_alpha, means, weights):
    return rho * sigma_alpha * np.sum(weights * means)

def lo_zhang_method(df):
    rho, sigma_alpha = estimate_parameters(df)

    N = len(df)
    means, variances, covariances = simulate_order_statistics(N)

    expected_alpha = compute_expected_alpha(rho, sigma_alpha, means, df['Portfolio Weight'])

    return expected_alpha
```